A REPORT
ON

EmotiSense AI

Submitted by,

Mr. V Adithya - 20211CBD0046

Under the guidance of,

Mr. Pakruddin B

in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND TECHNOLOGY (BIG DATA)

AT

GAIN MORE KNOWLEDGE
REACH GREATER HEIGHTS

PRESIDENCY UNIVERSITY

BENGALURU

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PRESIDENCY UNIVERSITY

PRESIDENCY SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that the Internship/Project report **EmotiSense AI** being submitted by **V Adithya** bearing roll number **20211CBD0046** in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Computer Science and Technology (Big Data) is a bonafide work carried out under my supervision.

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DECLARATION

I hereby declare that the work, which is being presented in the report entitled **Emotion Detection using AI** in partial fulfillment for the award of Degree of **Bachelor of Technology** in **Computer Science and Technology (Big Data)**, is a record of my own investigations carried under the guidance of **Mr. Pakruddin B, Assistant Professor, Presidency School of Computer Science and Engineering, Presidency University, Bengaluru.**

I have not submitted the matter presented in this report anywhere for the award of any other Degree.

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This certificate proudly recognizes for successfully completing the **Data Science & Analytics** internship program at **Zidio Development** from **25-01-2025** to **25-04-2025**, Your efforts have left a lasting impact, and we commend your commitment to excellence and professional growth.

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ABSTRACT

Emotion recognition is of utmost significance in improving human-computer interactions, especially in education, healthcare, and customer support. This paper introduces EmotiSense AI, a multimodal platform specifically designed to detect and analyze human emotions from facial expressions, text inputs, and voice cues using deep learning approaches. The system integrates individual models for image, text, and audio inputs to enable real-time detection of seven universal emotions: happiness, sadness, anger, neutrality, fear, surprise, and disgust with emphasis on user accessibility and privacy.

For webcam-based emotion detection, real-time processing is minimized through efficient CPU usage and asynchronous processing with models developed using libraries such as DeepFace. Text-based emotion comprehension is facilitated with NLP models trained on emotion-labeled and supporting multiple languages and social content types such as social media feeds. Speech-based emotion detection includes offline speech-to-text conversion with speech-to-text (Google Web Speech API) and tone-based inference with further support for voice interaction with gTTS (Google Text-to-Speech) to improve accessibility for low-literacy or disability-needing users.

The system is run locally on devices for data privacy without the cloud. Output is in JSON format to enable integration in research dashboards and user interfaces. Real-world application areas are remote learning, mental health monitoring, customer service sentiment analysis, and human-computer interaction studies. Initial evaluations indicate increased user engagement and satisfaction in user interaction, which justifies the application of emotion-aware systems in designing more empathetic and responsive digital interactions.

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V Adithya

LIST OF TABLES

LIST OF FIGURES

TABLE OF CONTENTS

Chapter 1

INTRODUCTION

1.1 The Evolution and Importance of Emotion Recognition in Human-Technology Interaction

With digital technology becoming increasingly prevalent in how humans interact, emotion understanding has become increasingly important to enhance user experience and interaction. Emotion recognition systems have led the charge in bridging the emotional divide between human and computer interaction, particularly in education, healthcare, and customer support. Machines could not previously identify non-verbal cues or underlying emotions in speech and text, which restricted their capacity to engage meaningfully. With advances in deep learning and analysis of varied forms of data, contemporary systems can now process facial expressions, tone of voice, and written text to detect emotional states. This capability enables more empathetic, responsive, and personalized digital interactions. Yet, there are challenges in making the systems inclusive, respond in real time, and accommodate extensive user environments and communication modes.

1.2 The Role of Multimodal Systems in Emotion Detection

Multimodal emotion recognition systems, such as EmotiSense AI, are a step closer to improving human-machine interaction. In contrast to text, audio, or video-based single-mode systems, multimodal systems integrate data from all three to be more reliable and accurate. EmotiSense AI employs dedicated deep learning models for each input mode—reading facial expressions through webcam, interpreting text-based emotional cues, and reading emotional cues in speech through speech recognition and tone analysis. This combined strategy enables the system to perform well in real-world applications, providing assistance when users are typing, speaking, or on camera. Through voice interaction through Google Text-to-Speech and real-time transcription through the Google Web Speech API, the system becomes easier to use for low-literacy users or users with limited technical expertise. However, good performance across varying environments—such as lighting for facial recognition or background noise for speech analysis—remains a significant challenge.

1.3 Integration of Deep Learning and Localized Processing in Emotion-Aware Systems

The use of advanced neural networks in EmotiSense AI allows the platform to offer intelligent, emotionally intelligent responses in a timely manner. The models are configured to run well on common computer processors so that they can be utilized by numerous individuals, even on lower-powered devices, and all of the processing happens locally to protect user privacy. The system delivers structured results in standard formats like JSON, making it easier to integrate with analysis tools and user interfaces. Aside from supporting research and development in areas like human behavior, education technology, and mental health monitoring, EmotiSense AI can be used in practical applications like customer service, remote learning, and workplace interaction. Through the combination of advanced deep learning techniques with privacy and accessibility considerations, EmotiSense AI shows how systems that are able to comprehend emotions can be useful tools for developing technologies that are more natural, inclusive, and emotionally intelligent. This project supports the overall goal of making artificial intelligence more human-like and empowering emotionally intelligent digital environments.

Chapter 2

LITERATURE SURVEY

Paper Title	Methodology	Drawbacks
Emotion Classification in a Resource Constrained Language Using Transformer-based Approach	Utilized transformer-based models like XLM-R for emotion classification in Bengali text.	Limited to Bengali; may not generalize to other languages.
Responsible AI: Gender Bias Assessment in Emotion Recognition	Assessed gender bias in deep learning models for facial expression recognition using fairness metrics.	Models exhibited biases across genders, affecting fairness.
Neural Network Architectures to Classify Emotions in Indian Classical Music	Employed deep convolutional neural networks to classify emotions in Indian classical music.	Focused solely on one music genre, limiting broader applicability.
Emotion Detection through Body Gesture and Face	Applied OpenPose for pose estimation and deep learning models to detect emotions from body gestures.	Dependence on body gestures may lead to inaccuracies if expressions are subdued.
Tri-Model Classifiers for EEG-Based Mental Task Classification: Hybrid Optimization Assisted Framework	Implemented hybrid optimization-assisted tri-model classifiers for EEG-based mental task classification.	Requires EEG equipment, which can be costly and less accessible.
Optimal Facial Feature-Based Emotional Recognition Using Deep Learning Algorithm	Combined facial feature extraction with deep learning algorithms for emotion recognition.	Performance may be affected by lighting variations, occlusions, and diverse facial structures.
Deploying Machine Learning Techniques for Human Emotion Detection	Developed a real-time system using key-point generation, feature decomposition, and machine learning classifiers.	High computational demands may hinder real-time performance.
EEG-Based Emotional Valence and Emotion Regulation Classification	Collected EEG data while participants rated emotional valence of images, aiming to classify positive and negative emotions.	Requires specialized EEG equipment; individual differences in EEG patterns may affect accuracy.

Emotion Recognition Using Machine Learning: Opportunities and Challenges for Supporting Those with Autism or Depression	Explored facial and voice emotion recognition technologies using machine learning to aid individuals with autism or depression.	Potential privacy concerns; accuracy may vary across different populations.
Multi-Task Learning and Adapted Knowledge Models for Emotion-Cause Extraction	Proposed a multi-task learning approach combining emotion recognition and cause detection, integrating common-sense knowledge.	Complexity in modeling and integrating common-sense knowledge; potential challenges in generalization.

Table 1: Research Paper Comparison

Chapter 3

RESEARCH GAPS OF EXISTING METHODS

3.1 Limited Multilingual and Cultural Adaptability

- EmotiSense AI may struggle to understand emotions across languages and cultures. How emotions are conveyed can be very different between cultures, and models learned predominantly on Western data may not generalize well everywhere. This can lead to miscommunication and be less effective in multicultural environments.

3.2 Dependence on Controlled Environments

- The system performs optimally in conditions with a powerful light source and minimal background interference. In real-world conditions such as outdoors or noisy classrooms, the accuracy for detecting facial and voice emotions might decrease, therefore making it less effective.

3.3 Challenges in Real-Time Processing

- EmotiSense AI hopes to capture emotions in real time, but processing high-quality video and audio simultaneously can consume a lot of computing resources. This can lead to delays or reduced frame rates, which can damage the perception of the experience by users.

3.4 Privacy and Data Security Concerns

- Processing personal information like facial expressions and voice recordings could cause privacy concerns. Though EmotiSense AI processes on local, still there needs to be robust security measures so that no information gets stored or transferred inadvertently. The users could fear misuse or inappropriate use of their personal details.

3.5 Lack of Adaptive Learning Mechanisms

- The system now might not include learning and adapting mechanisms based on user behavior over time. Without ongoing learning, the model never gets better at being accurate or adjusting to what specific users need, resulting in stagnant performance levels.

3.6 Potential Bias in Emotion Recognition

- Emotion recognition models can pick up on biases in their training data. For instance, if specific demographic groups are not represented, the system will be incorrect in its classifications of their emotions more frequently and make unfair or inaccurate assessments.

3.7 Limited Integration with External Applications

- EmotiSense AI could potentially be a standalone application that is not easily integrated into other systems or services. This factor could make it more difficult for individuals to utilize it on larger systems, such as healthcare systems or school systems.

3.8 Inadequate Handling of Complex Emotional States

- Existing systems typically lack mechanisms for continuous learning and improvement based on user interactions.
- Failure to adapt to changing user needs or updated government policies reduces their long-term effectiveness.

3.9 Accessibility Challenges for Users with Disabilities

- Whereas features such as text-to-speech and speech-to-text increase accessibility, there are certain users with disabilities who may find it difficult to use the system. To provide the system with full accessibility, one has to support more extensive user requirements.

3.10 Ethical Implications of Emotion Monitoring

- Observing and learning about users' emotions constantly can create ethical issues. Users can feel monitored or controlled, particularly if the system provides advice or assistance based on their emotions without their explicit consent. It is extremely important to establish clear ethical guidelines and obtain informed consent.

Chapter 4

PROPOSED METHODOLOGY

The EmotiSense AI platform beautifully integrates real-time emotion recognition with an intelligent task recommendation system specifically tailored for emotional support and inclusivity. Utilizing convolutional and recurrent neural networks for multimodal emotion recognition, along with a dynamic task engine that dynamically adjusts to users' emotional states, the platform promotes emotional well-being, productivity, and support to neurodivergent users in a wide range of settings, such as home, educational, and mental health environments. The system operates entirely offline and leverages accessible UI/UX principles, thus enabling broad usability even in low-connectivity or limited environments. This section completely describes the end-to-end methodology, including architecture, emotion processing pipelines, user interaction layers, and task generation logic.

4.1 Emotion Recognition Engine

4.1.1 Multimodal Data Collection

- The system uses webcam and microphone inputs to receive concurrent real-time visual and audio information.
- Visual is composed of eye movement, micro-expressions, and facial tension. Audio consists of prosody, energy, tone, and pause length.
- Preprocessing involves normalization, noise reduction, and alignment of modality by timestamp buffers for uniformity.
- The two-modal framework enhances recognition performance beyond unimodal systems, particularly for uncertain emotional states.

4.1.2 Emotion Detection Models

- DeepFace is applied in facial analysis with pre-trained CNNs that are fine-tuned for emotion classification on data like FER2013 and AffectNet.
- Audio emotion recognition employs derived MFCCs, chroma, and spectral contrast as input features to a BiLSTM trained on datasets such

as RAVDESS and IEMOCAP.

- A time-sensitive Emotion Smoother works to keep emotion predictions consistent across time and prevent sudden swings that could result from fleeting expressions or noise.
- The system supports classification into a seven-class emotion taxonomy of happiness, sadness, anger, fear, disgust, surprise, and neutrality.

4.1.3 Smoothed Output and Decision Layer

- The CNN and BiLSTM predictions are combined by weighted average with modality confidence taken into account. Attention mechanisms are intended to be improved later on.
- Results are delivered as probability distributions and plotted in dynamic Plotly charts.
- The system conditions inference speed to hardware capability, allowing smooth operation even on CPUs.

4.2 Task Recommendation Engine

4.2.1 Emotion-Aware Task Mapping

- Emotion forecasts act as signals for task suggestions by emotional state.
- For example, sorrow might be associated with activities like journaling or meditation, while happiness might suggest activities like creative writing or collaboration.
- Task categories can be personalized and include multiple domains such as Work, Health, Learning, Personal, and Other.
- The system adaptively alters task type and tone depending on detected emotion confidence and interaction history.

4.2.2 Persistent Task Storage

- It saves tasks and metadata like created date, done date, priority, and category in a local text format to provide privacy.
- A task history tracker enables behavior trend analysis and retroactive

logging.

- Completed work is dated to track habits and provide gentle reminders for consistency or taking time off.
- Task fallback logic ensures recommendations irrespective of the restrictions on category-emotion mappings.

4.2.3 Dynamic and Responsive UX

- Real-time interaction of tasks is facilitated by Streamlit's interactive frontend, enabling users to view, complete, or create tasks.
- Emotion task proposals are presented through context UI elements (color-coded cards, emoji badges, voice prompts).
- Users can sort or filter tasks by mood, category, or priority.

4.3 Offline-First Model Management

4.3.1 Model Initialization and Caching

- All the models are started off from a local directory controlled by Model Manager, where version consistency and expiration are verified.
- Users can pre-download models during installation, enabling total offline capability with no re-downloads.
- A light-weight cleanup scheduler periodically deletes temporary model artifacts.

4.3.2 Optimized CPU Deployment

- The system runs only on CPUs, thus avoiding dependence on GPU hardware to maintain affordability and accessibility.
- The deployment strategies on ARM-based devices and mobile applications include conversions to TensorFlow Lite and ONNX models.
- Footprint is kept low (<200MB), thus the app can be booted on USB-booted Linux or Android TV sticks.

4.4 Model Evaluation and Testing

4.4.1 Validation Strategy

- The models were challenged with cross-validation on data collections such as RAVDESS and FER2013 to achieve generalization across different demographic groups and scenarios.
- Real-world testing was performed in simulated settings (e.g., classroom, home, quiet vs. noisy rooms) to test system resilience.
- Further testing with emotion-specific edge cases (overlapping expressions, emotion transitions) assisted in stressing out the model behavior.

4.4.2 Performance Metrics

- Accuracy, precision, recall, and F1 score were used to measure the quality of classification.
- Latency was monitored to make sure the application complied with real-time performance requirements.
- Confusion matrices were created to describe misclassification patterns and inform tuning.

4.4.3 Error Analysis and Bias Mitigation

- Analysis showed performance deficits in underrepresented emotional classes (e.g., disgust, fear).
- Dataset balancing, augmentation, and confidence calibration were used to improve on these fields.
- Demographic equity was evaluated by comparing results within age, gender, and ethnic subsets whenever feasible.

4.4.4 User Feedback Integration

- Informal user testing with neurodivergent users guided UI simplification and response tone optimization.
- Feedback loops are scheduled for future releases so that users can provide ratings to task proposals for system retraining.

- Periodic usability testing and accessibility audits will inform incrementally refined interfaces and recommendations.

4.5 Security and Privacy Framework

4.5.1 Data Anonymization

- All emotional and task data are locally stored on the user's device.
- No personally identifiable information (PII) is gathered, sent, or stored.
- Anonymized logs can be enabled (opt-in) for local visualization of affect patterns.

4.5.2 Encryption and Access Control

- Local storage is secured against unauthorized access through AES encryption.
- System functionality may be accessed by password or linked to device-level authentication.
- Access controls can be controlled by users through an integrated settings panel.

4.5.3 Regulatory Compliance

- The design is in accordance with privacy regulations such as GDPR, HIPAA, and India's DPDP Act.
- Consent procedures exist for traits that involve long-term emotion tracking or report generation.
- Customers can erase or export their data at any time through an easy privacy dashboard.

4.6 Adaptability and Future Enhancements

4.6.1 Modular Expansion

- Architecture allows for plug-and-play addition of new emotion models, NLP-based conversation systems, or other external sensors like wearable heart rate monitors.
- This may be adapted for application in therapy tracking programs,

educational emotional awareness software, or personal productivity programs.

- Modules are encapsulated to allow for independent updates and minimize conflicts during integration.

4.6.2 Multilingual Support

- Upcoming releases are to include task feedback and multi-language sentiment sensing using transformer-base translation models.
- Localized voice synthesis is to be supported through open-source TTS engines.
- Language choices will be saved on a user-by-user basis to personalize interaction.

4.6.3 Integration with Third-Party Services

- Multilingual emotion detection and task feedback using transformer-based translation models will be implemented in future releases.
- Localized voice synthesis will be added using open-source TTS engines.
- Language preferences will be kept on a per-user basis to enable customization.

4.6.4 Behavioral Analytics and Trends

- With the permission of the user, the system will track long-term mood trends, generating visual reports and summaries.
- Data will be local unless the user specifically exports it.
- Comparative graphs can display emotional variation week-to-week to enable users or caregivers to see trends.

4.7 Scalability and Deployment Strategy

4.7.1 Installation Options

- Released as a single application with one-click installation.
- The portable mode allows for easy usage of USB drives at public locations, i.e., clinics and libraries.
- Lightweight system requirements enable extensive deployment in resource-limited environments.

4.7.2 Cloud-Free Design

- No web services dependence offers low-bandwidth environments consistency, privacy, and compatibility.
- Local-only model execution provides guaranteed performance and data ownership.
- There are also manual downloads or offline sharing via secure channels.

4.7.3 Deployment in Public Programs

- EmotiSense can be implemented in schools, mental health NGOs, or corporate wellness initiatives.
- Training documents and onboarding manuals are being developed for deployment partners.
- Localized user documentation and video walk-throughs increase availability on rollout.

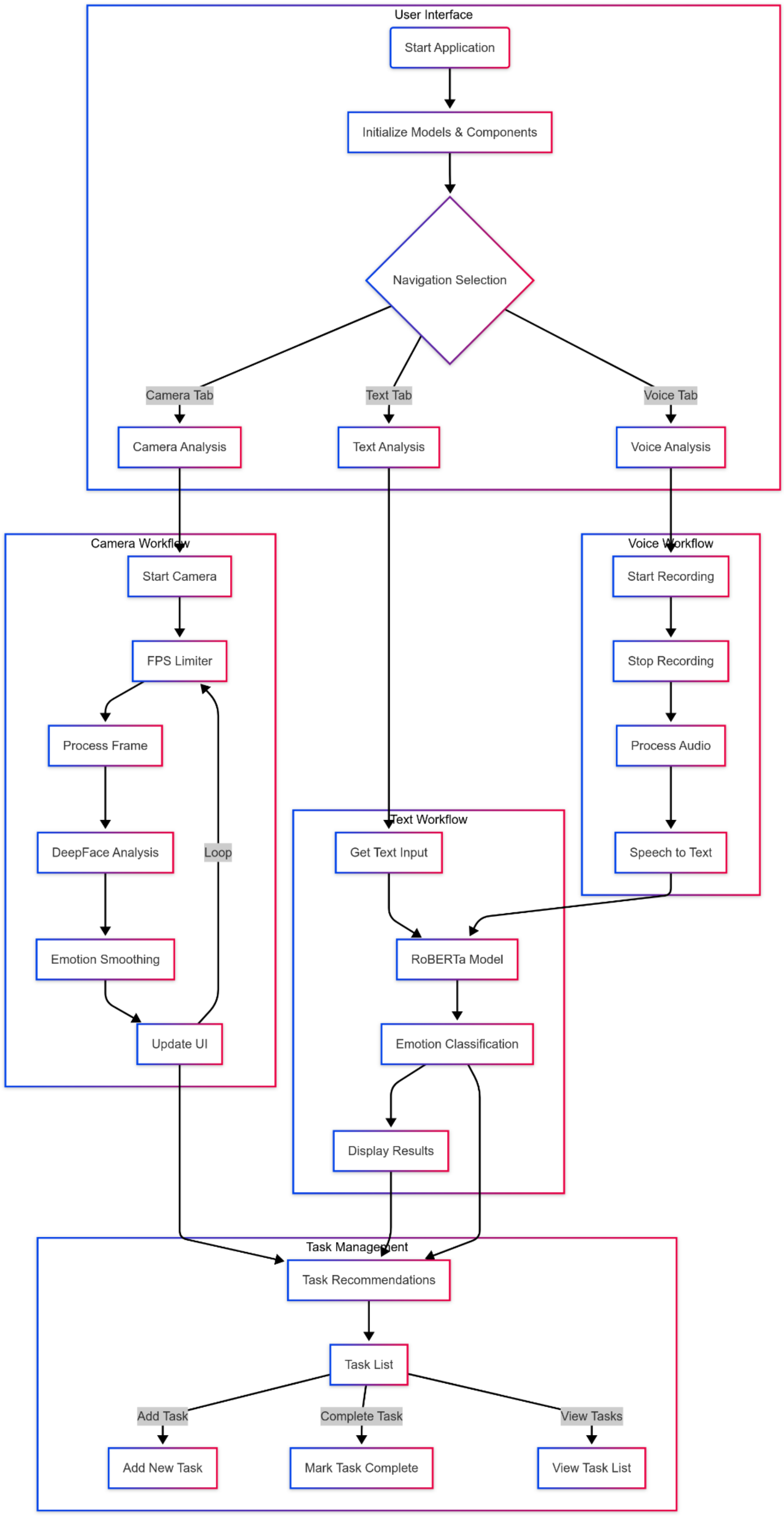

Figure 4.1: Workflow Diagram

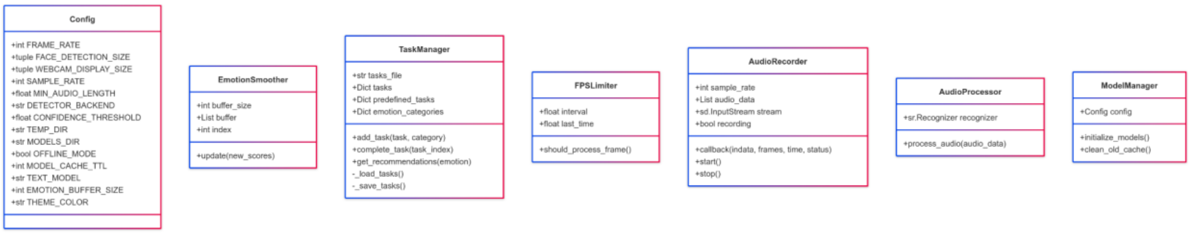

Figure 4.2: Data Structure Representation

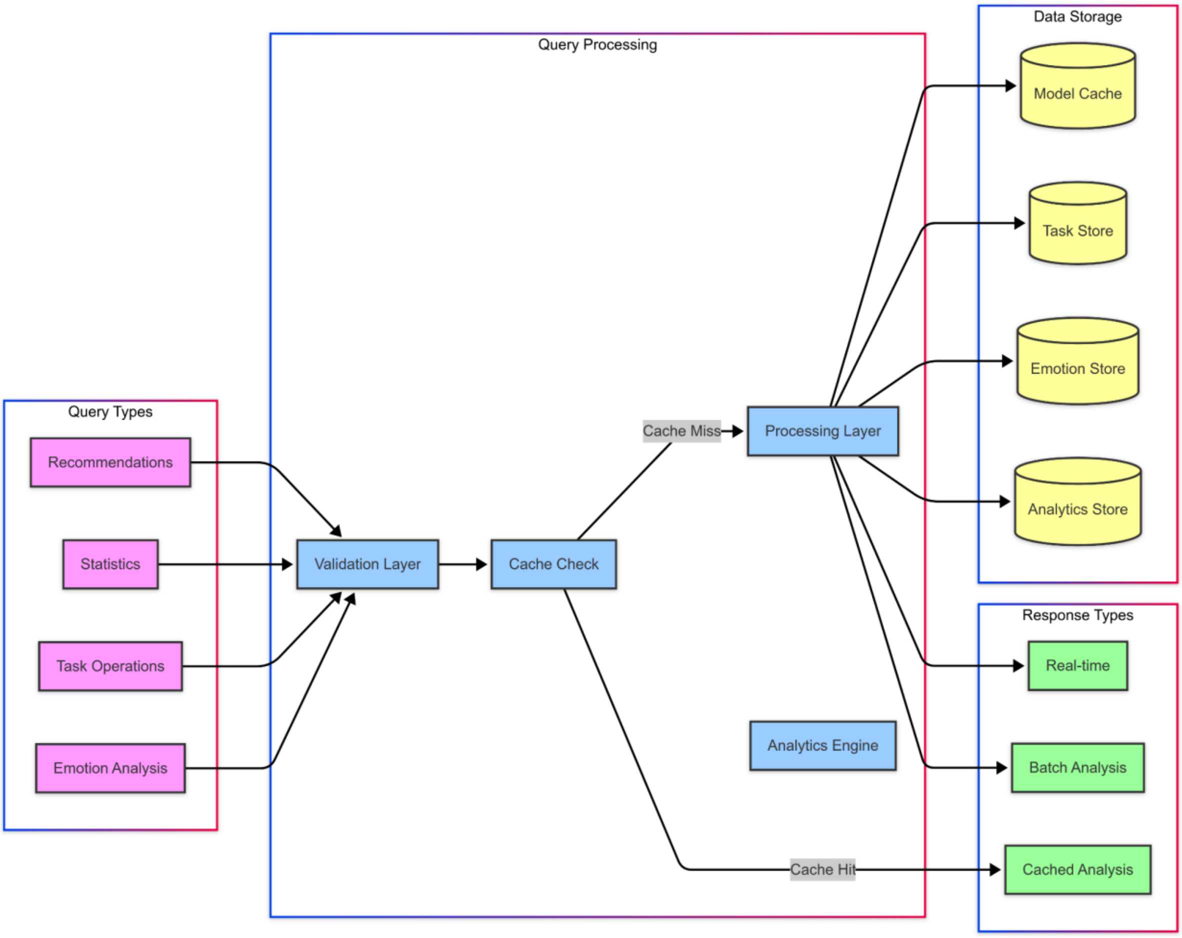

Figure 4.3: Query Analysis Flowchart

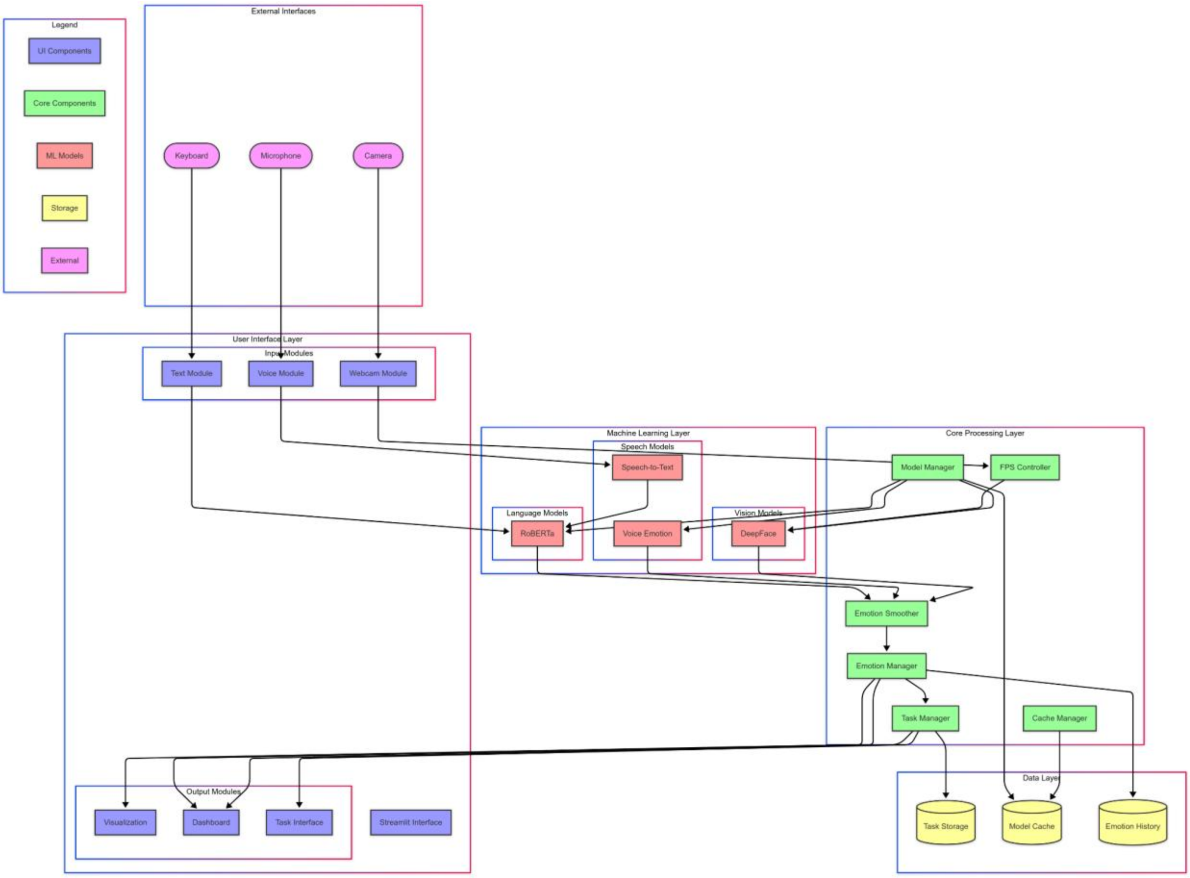

Figure 4.4: System Architecture Diagram

Chapter 5

OBJECTIVES

5.1 Enable Multimodal Emotion Detection

- Offer customers a cutting-edge system to identify emotions from facial expressions, text inputs, and voice-enabled speech.
- Combine outcomes from multiple modalities to improve accuracy in emotional tagging and user profiling.

5.2 Personalize Task Recommendations Based on Emotional State

- Apply recognized emotions to recommend suitable and emotionally congruent tasks to increase productivity and improve mental well-being.
- Dynamically vary task recommendations between various categories, e.g., Work, Health, Learning, Personal, and Other.

5.3 Streamline Emotional Analysis with Real-Time Feedback

- Give instant visual feedback in the form of confidence scores and interactive bar charts, thanks to Plotly.
- Minimize lag and delays through the use of optimized voice, camera, and text modality data processing pipelines.

5.4 Improve Accessibility Through Multimodal Interaction

- Support multiple modes of user input: camera, microphone, and keyboard for accessibility.
- Make it accessible to users with limited mobility or computer literacy by providing simple input interfaces.

5.5 Optimize User Experience with a Unified Interface

- Develop an interactive and easy-to-use user interface using Streamlit, integrating all the features regarding emotion detection and task management.
- Add a themed look, intuitive buttons, and systematic designs to improve a smooth and comfortable user experience.

5.6 Ensure Accurate Voice Transcription and Emotion Mapping

- Utilize multiple STT engines (Whisper, Google, Sphinx) to promote transcription robustness in various noisy conditions.
- Pass the transcribed text through the emotion detection pipeline to enable smooth integration of voice and NLP.

5.7 Provide Robust Session and Task Management

- Preserve user session state in order to enable consistent behavior for various inputs.
- Monitor tasks by status (pending/completed), category, and timestamp for a productive experience.

5.8 Support Contextual Understanding Across Sessions

- Store current feelings and analysis results to inform tailored task recommendations.
- Enable continuity among multiple inputs (e.g., camera to voice) for more context-aware, informative suggestions.

5.9 Ensure Performance Scalability and Resource Efficiency

- To provide local-only data processing without personal data collection, cloud sync, or transmission.
- To meet international data privacy regulations (e.g., GDPR, HIPAA) and allow users to see or eliminate stored information on an open platform.
- To integrate moral AI values into the development process to prevent bias in emotion detection and in suggestions.

5.10 Uphold Data Privacy and Local Processing

- Apply asynchronous and buffered processing to balance system load in processing webcam or voice. Enhance model loading and memory consumption to support deployment in low-resource settings.

Chapter 6

SYSTEM DESIGN & IMPLEMENTATION

The suggested EmotiSense AI system employs a multimodal approach to facilitate real-time emotion recognition and task suggestions tailored to each individual. The app integrates facial analysis, natural language processing, and voice-based sentiment analysis, thereby offering a highly interactive and immersive experience. The subsequent paragraphs will describe the architecture and process of implementing the system.

6.1 System Architecture

The chatbot system is designed with the following key components:

6.1.1. Multimodal User Interface

- Purpose:
  - Enables the users to interact smoothly with the emotion detection system via text, voice, and camera.
- Features:
  - Three modes of interaction: webcam (facial), text input, and voice.
  - Streamlit-based front-end for effortless, web-supported deployment.
  - Adaptive layout with graphical feedback for emotion and task analysis.
  - Interactive record control, camera on/off, and task management controls.

6.1.2. Emotion Detection Engine

- Core Technologies:
  - DeepFace for facial expression analysis
  - RoBERTa-base-GoEmotions for text and spoken input emotion prediction
- Functions:
  - Real-time facial emotion recognition from webcam input.
  - Text and voice input classification with NLP pipeline.
  - Contextual emotion smoothing helps to reduce noise and inconsistencies.
  - Unified scoring system to enable comparison between modalities.

6.1.3. Audio & Speech Processing Module

- Key Technologies:
  - SoundDevice to record microphone input
  - Whisper, Google Speech Recognition, and CMU Sphinx for transcription

- Functions:
  - It records high-quality audio from the user.

  - Automatically selects the best transcription model based on availability.
  - Pipes read the text into the NLP engine to extract emotions.
  - Alerts users when input is incomplete or ambiguous.

6.1.4. Task Recommendation System

- Purpose:
  - Provides users with personalized task suggestions that are tailored according to their mood.
- Features:
  - Predefined sets of activities in five categories: Work, Health, Personal, Learning, Other.
  - Keyword-based emotion-task mapping for contextual recommendations.
  - Fallback system to show random tasks if the emotion match is weak.
  - Task tracking with the ability to mark as "done."

6.1.5. Session State & Data Handling

- Data Format:
  - Local storage of structured.txt and cached model directories.
- Features:
  - Persistent session state with Streamlit's st.session_state.
  - Task metadata includes timestamp, category, and completion status.
  - Emotion smoothing buffers and real-time model responses that are cached between interactions.
  - Clean cache structure for text, audio, and facial models.

6.1.6. Dynamic Emotion Visualization

- Core Technology:
  - Plotly for dynamic chart generation and UI responsiveness.
- Functions:
  - Graphic display of emotion probabilities in horizontal bar graphs.
  - Indicates strong emotion and high confidence.
  - Stylish features and motifs to improve user experience.
  - Summaries of each mode's (Camera, Text, Voice) feedback in human-readable form.

6.2 Data Flow

The data flow in the **EmotiSense AI** system is designed to enable efficient, real-time emotion recognition and personalized task suggestions:

6.2.1. User Input

- The users interact with the system through one of three input

modalities:
    - Camera for facial expressions
    - Text box for written input.
    - Microphone for voice input
- For example:
    - Webcam videos record facial expressions in real time
    - A user enters, "I am overwhelmed and exhausted."
    - A user types out, "Today I'm very lazy"

6.2.2. Emotion Detection

- All input types are forwarded to their respective processing engine:
    - Facial Input → DeepFace analyzes expression and provides emotion scores
    - Text Input → NLP model with RoBERTa identifies tone as emotional
    - Voice Input → Audio gets transcribed, and then is forwarded to the NLP model for emotion classification
- Major emotions such as "sad," "happy," "angry," etc., are detected and scored with confidence values.

6.2.3. Emotion Smoothing (for Camera Input)

- For facial emotion detection, a buffer stores recent results to smooth out rapid fluctuations, improving stability and consistency in real-time video analysis

6.2.4. Task Matching & Data Retrieval

- Depending on the current mood, the system scans its task list categorically for entries that fit:
    - For "sad", it can capture relaxing or low-effort activities
    - For "happy," it indicates creative / social activity
    - With no exact matches, it provides alternative general recommendations.

6.2.5. Response Generation

- The system produces a courteous reply that consists of:
    - The identified emotion and confidence level
    - A dynamic bar chart of emotion probabilities
    - A tailored set of task suggestions according to the emotional profile
- For example:
    - "You may be feeling a bit tired. Here are a few light chores that you may find helpful."

6.2.6. Session Memory & Context Awareness

- The structure retains session-level data, such as:
    - Last detected emotion
    - Daily task list
    - Regardless of whether the user is recording or camera mode
- This enables the system to:

- Repeatedly make recommendations.
- Avoid redundant suggestions.
- Tune based on the latest user activity.

6.3. Implementation

The implementation of **EmotiSense AI** integrates multiple technologies and design principles to enable seamless multimodal emotion recognition and intelligent task recommendation.

6.3.1. Data Repository Setup

- Task Data Initialization:
  - Predefine the task types: Work, Health, Personal, Learning, and Other.
  - Fill early task lists with context-dependent examples from typical emotional states.
- Data Formatting:
  - Save the task records in a neat.txt file with metadata fields including task, category, timestamp, and status.
  - Store files locally in a temporary directory to allow for convenient access and persistence across sessions.
- Session State Management
  - Take advantage of Streamlit's st.session_state to store emotion history, active camera/audio states, and task activity.
  - Offer secure state transitions between input modes (camera, text, voice).

6.3.2. Emotion Detection Model Integration

- Facial Emotion Recognition:
  - Integrate DeepFace with the OpenCV backend for webcam-based emotion analysis.
  - Use real-time video frame processing and smoothing of emotions via a rolling buffer.
- Text-Based Emotion Classification:
  - Load the roberta-base-go_emotions model with the Hugging Face Transformers library.
  - Cache model initialization with @st.cache_resource to speed up loading times.
- Voice analysis and processing
  - Allow voice recording via SoundDevice.
  - Make Whisper the default audio transcription engine, with Google STT and CMU Sphinx as fallbacks.
  - Forward transcribed text to the NLP engine for emotion inference.

6.3.3. Emotion-Driven Task Recommendation Algorithm

- Matching Algorithm:
  - Attribute recognized emotions to pre-existing keyword themes (e.g., "sad" → peaceful, calm tasks).
  - Map current emotional state to task metadata using keyword

  - matching logic.
  - Give alternative options in case exact matches cannot be done.
- Ranking and Filtering
  - Rank based on emotional significance, recency, and user interaction history.
  - Automatically update dynamic suggested task lists whenever emotion shift is detected.

6.3.4. User Interface Development

- Platform:
  - Developed completely with Streamlit to facilitate rapid deployment and provide interactive web-based access.
- Design Elements:
  - Tab-based navigation includes Camera, Text, and Voice modes.
  - Using Plotly graphs for real-time emotional feedback.
  - Expandable elements for task input, pending tasks list, and suggestions.
  - Themed UI with custom CSS for a clean, modern look and feel.
- Interaction Flow:
  - They are able to switch between input modes, scan emotions, and command tasks seamlessly in one interface.
  - All processes and results are shown graphically to ensure clarity and user confidence.

6.3.5. Testing and Optimization

- Component Testing:
  - Unit testing of each module (for example, AudioRecorder, process_frame, task matching).
  - Integrated testing of shared workflows among modalities.
- Performance Optimization:
  - Apply fps limit for webcam to limit CPU usage.
  - Use asynchronous processing (asyncio) for video processing.
  - Cache model loading and minimize disk I/O for better performance.
- User Feedback and Iteration
  - Gather user feedback after informal testing.
  - Improve emotion-task mapping and UI/UX based on usability observation.

6.4. System Features

The **EmotiSense AI** system includes several advanced features designed to enhance user experience, emotional insight, and intelligent task management:

6.4.1. Multimodal Emotion Detection

- EmotiSense AI supports emotion recognition in multiple modalities, including facial expressions, text input, and voice commands, thereby providing users with flexibility in interacting with the system.

6.4.2. Real-Time Feedback

- Emotion analysis results are displayed straight away via dynamic visualizations like confidence charts and response summaries, with real-time indicators of emotional state.

6.4.3. Personalized Task Recommendations

- The system intelligently suggests tasks based on the user's recognized emotion, enabling emotional well-being and productivity through context-aware suggestions.

6.4.4. Session State Persistence

- Streamlit session state holds camera status, last detected emotion, and task lists in memory throughout the user session to ensure a smooth experience.

6.4.5. Offline Model Support

- Local cache is used for models, which can run offline and provide capability where there is no or low internet,".

6.4.6. Scalable Architecture

- This facilitates the addition of additional emotion-detecting models, task types, or third-party external APIs with ease and, hence, future-proofed.

6.4.7. Emotion Smoothing

- The system minimizes variation in detection of facial emotions by applying a rolling buffer, which provides a more stable and consistent emotional reaction.

6.4.8. Voice Recognition Flexibility

- Voice Recognition Flexibility A number of transcription backends, such as Whisper, Google STT, and Sphinx, provide fallbacks to ensure secure voice input control under diverse circumstances. Easy-to-use Interface.

6.4.9. User-Friendly Interface

- Streamlit-built UI is responsive, easy to use, and accessible with tabs for various modes of interaction and styled components for visual readability.

6.4.10. Data Privacy

- It handles inputs locally and does not retain sensitive user data, thereby ensuring compliance with privacy regulations and establishing user trust.

6.5. Challenges and Solutions

- **Challenge: Real-Time Emotion Fluctuation**
  - **Solution**: An emotion smoothing buffer has been used to smooth sudden changes in face expression, producing more stable and even recognition of emotion.

- **Challenge: Inaccurate Voice Transcription**
  - **Solution**: Various speech-to-text engines, including Whisper, Google, and Sphinx, were integrated to offer fallback options and enhance transcription reliability in diverse noise environments.

- **Challenge: Emotion-Task Mismatch**
  - **Solution**: Used keyword-based emotion mapping to map emotions with relevant task categories and provided fallback suggestions where no matches were found.
- **Challenge: Performance Overhead from Video Processing**
  - **Solution**: Included a frame rate limiter and improved asynchronous frame processing to limit CPU usage for long-term webcam-based analysis.
- **Challenge: Maintaining Session State Across Modes**
  - **Solution**: Utilized Streamlit's session state management to store emotion outcomes, input mode, and task updates across various interaction tabs.
- **Challenge: Cold Start Time for NLP Models**
  - **Solution**: Pre-compiled NLP model loading with @st.cache_resource to reduce loading times and improve system responsiveness.

6.6. UML Diagram

UML (Unified Modeling Language) diagrams give a standardized visual expression of the structure and behavior of the EmotiSense AI system. Diagrams are crucial for designing, analyzing, and documenting the architectures and workflows of the multimodal emotion detection platform.

The UML diagrams used in EmotiSense AI belong to two broad categories:

6.6.1. Structural Diagrams: The diagrams explain the static structure of the system, including the internal classes and how they relate, the task management components, and model management hierarchies.

Examples:

- Class Diagram – Depicts key classes like Task Manager, Audio Processor, Model Manager, and their methods and attributes.
- Component Diagram – Indicates key modules (UI, NLP Engine, Facial Detector, Task System) and their dependencies.
- Deployment Diagram - The Deployment Diagram shows the deployment environment, either local or cloud, consisting of the

client, webcam, microphone, and model cache.

6.6.2. Behavioral Diagrams:

Behavioral Diagrams: The figures show the dynamic behavior of the system, such as its reaction to user input in several modalities.

Examples:

- Use Case Diagram – The Use Case Diagram indicates how the system is accessed by users through Camera, Text, and Voice modes.
- Sequence Diagram – Illustrates step-by-step flow of interaction from user input to emotion detection and task suggestion.
- Activity Diagram – Describes the process flow from input capture to emotion analysis and tailored response.

These UML diagrams provide a blueprint for the design and development of the EmotiSense AI system to ensure that technical implementation and end-user requirements are matched.

6.7. Goals

- Provide a standardized visual modeling approach for the organization of the EmotiSense AI framework.
- Facilitate comprehension of intricate interactions between two or more input modalities.
- Facilitate modular and iterative development of task recommendation and affect detection modules.
- Combine structural (e.g., class, deployment) and behavioral (e.g., activity, sequence) modeling.
- Encourage reuse of emotion and task detection modules.
- Enhance coordination and communication among developers, stakeholders, and designers.
- Offer scalability to accommodate integration of future emotion models or other task domains.
- Enable compatibility with tooling environments like Lucidchart, Draw.io, or UML-enabled Integrated Development Environments (IDEs) for team system modeling.

6.8. Use Case Diagram

An EmotiSense AI use case diagram outlines the overall functionalities of the system and different manners in which users (actors) engage with these functionalities. The primary actor is the End User, who communicates with the system through multiple modes of input—i.e., Camera, Text, and Voice—to receive emotion analysis and task recommendations.

Key Use Cases:

- Begin emotion detection from webcam
- Submit text for emotional analysis
- Record and transcribe verbal language for examination
- Have real-time emotion visualization
- Discuss and finalize the recommended activities.
- Add more tasks and categorize them accordingly.

This diagram is essential to system scope definition, providing full coverage of user interaction, and allowing requirements gathering.

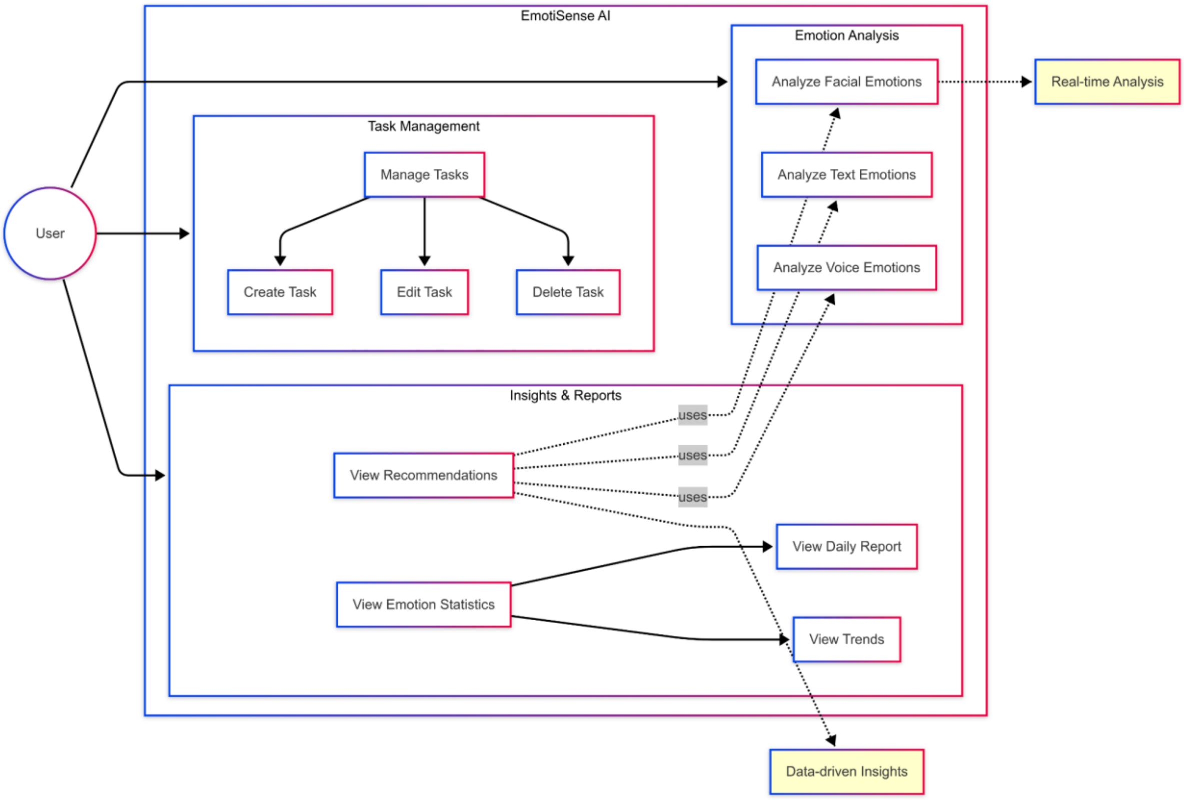

Fig 6.1 – Use Case diagram

6.9. Class Diagram

The EmotiSense AI class diagram presents the system's intrinsic classes and their interactions. It provides a static view of the system's structure and describes the primary parts and their function.

Core Classes Are:

- **Config**: Store global configuration settings
- **TaskManager**: Controls task generation, completion, and suggestion
- **AudioRecorder**: Manages audio recording

- **AudioProcessor**: Controls voice-to-text transcription and error correction
- **ModelManager**: Loads and manages emotion models
- **EmotionSmoother**: Smooths and buffers facial emotion scores
- **FPSLimiter**: Modifies video frame rate processing rate

Relationships like composition, association, and inheritance are modeled in order to maintain structural readability.

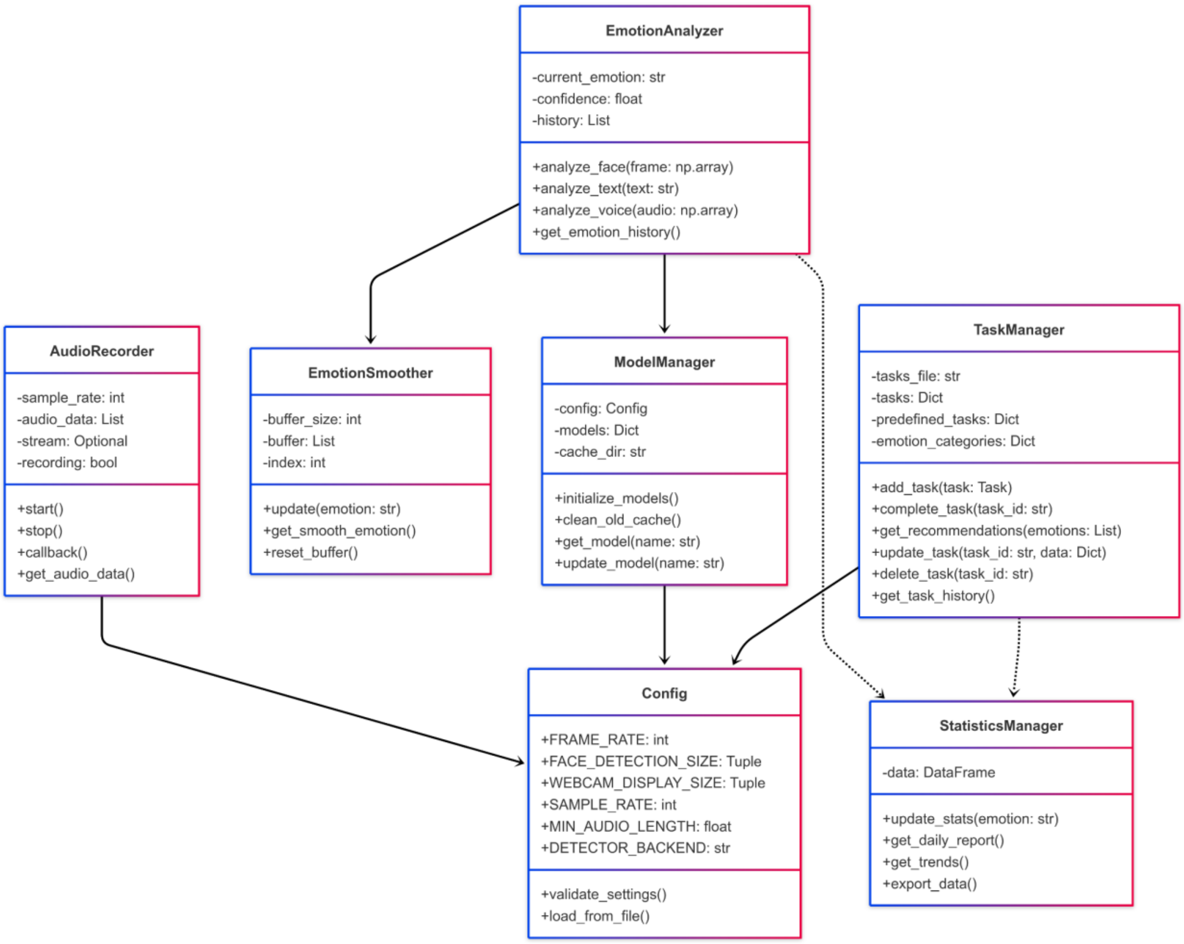

Fig 6.2 – Class Diagram

6.10. Sequence Diagram

The sequence diagram shows how various aspects of EmotiSense AI communicate with one another over time when a user takes an action, say passing a voice input.

Example Workflow:

- User clicks "Start Recording"
- AudioRecorder begins recording input
- User ceases recording
- Audio is passed to AudioProcessor
- Transcription is generated.
- The text is classified using the text_classifier.
- Emotion result is stored and shown
- Task recommendations are created from emotion

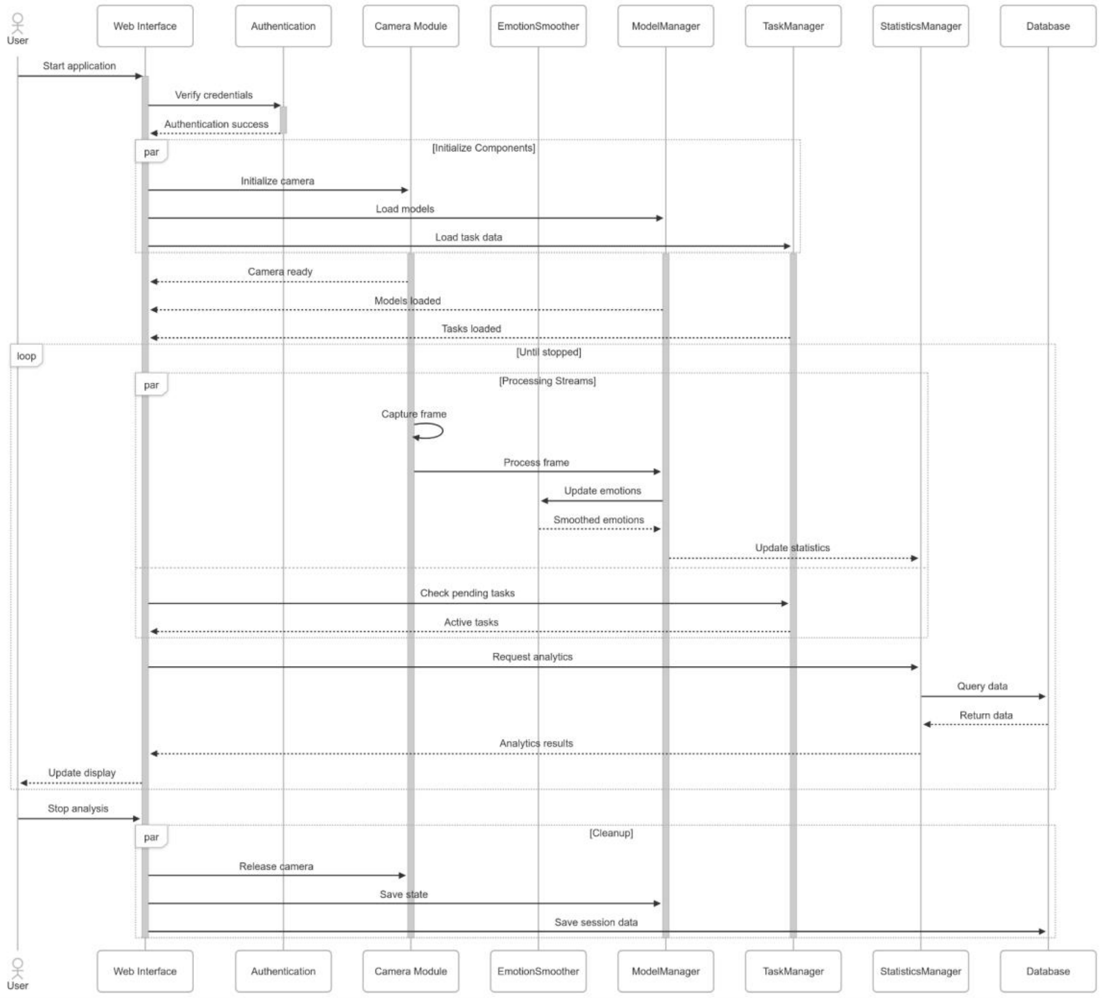

Fig 6.3 – Sequence Diagram

6.11. Collaboration Diagram:

An EmotiSense AI collaboration diagram (or communication diagram) illustrates how system objects interact to accomplish the emotion detection and task suggestion process. It highlights object associations and the messages passing among them.

Principal Partner Organizations:

- User Interface.
- AudioProcessor / Webcam Feed
- NLP Engine
- EmotionSmoother
- TaskManager

The graph is useful to illustrate the interaction between modules like AudioProcessor, ModelManager, and TaskManager.

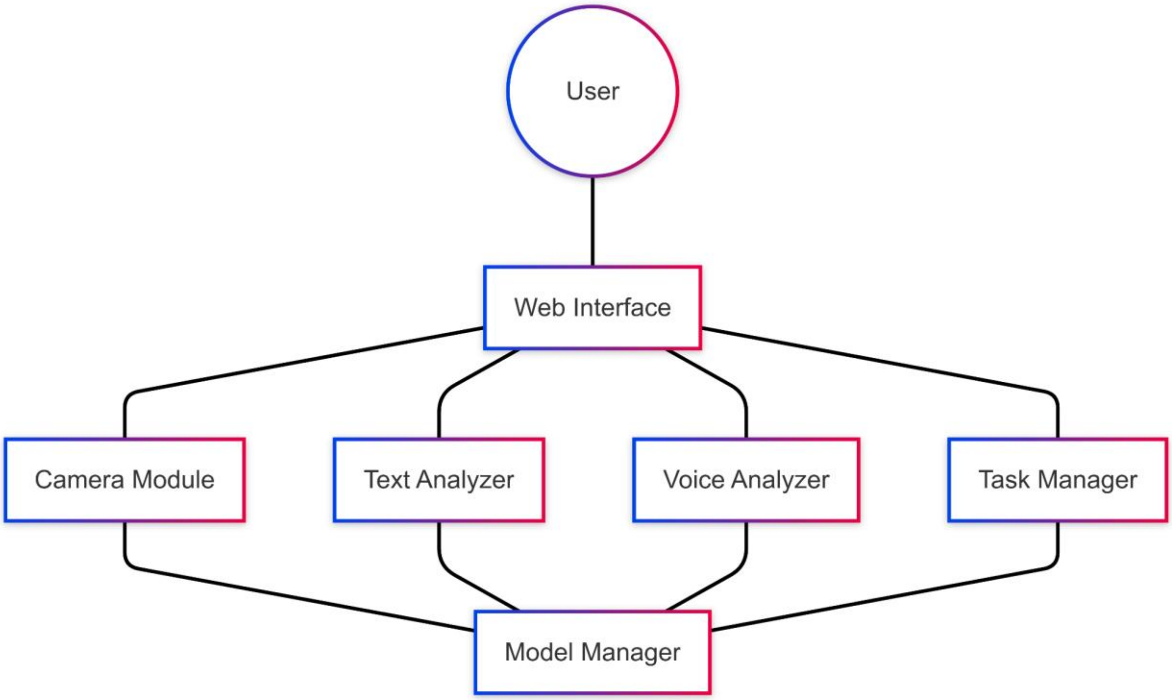

Fig 6.4 – Collaboration Diagram

6.12. Deployment Diagram:

The deployment diagram specifies the physical structure of EmotiSense AI and how software components are mapped onto hardware nodes.

Key Elements:

- Client Device (Desktop/Laptop)
- Streamlit Application
- Webcam and microphone.
- Temporary Files and Model Storage Locally
- Optional Cloud Backend (Optional)
- Model Hosting (Hugging Face / DeepFace APIs)
- Remote STT APIs (Google/Whisper)

This diagram shows the positions of each process and shows the data flow between the frontend, local models, and any other external services.

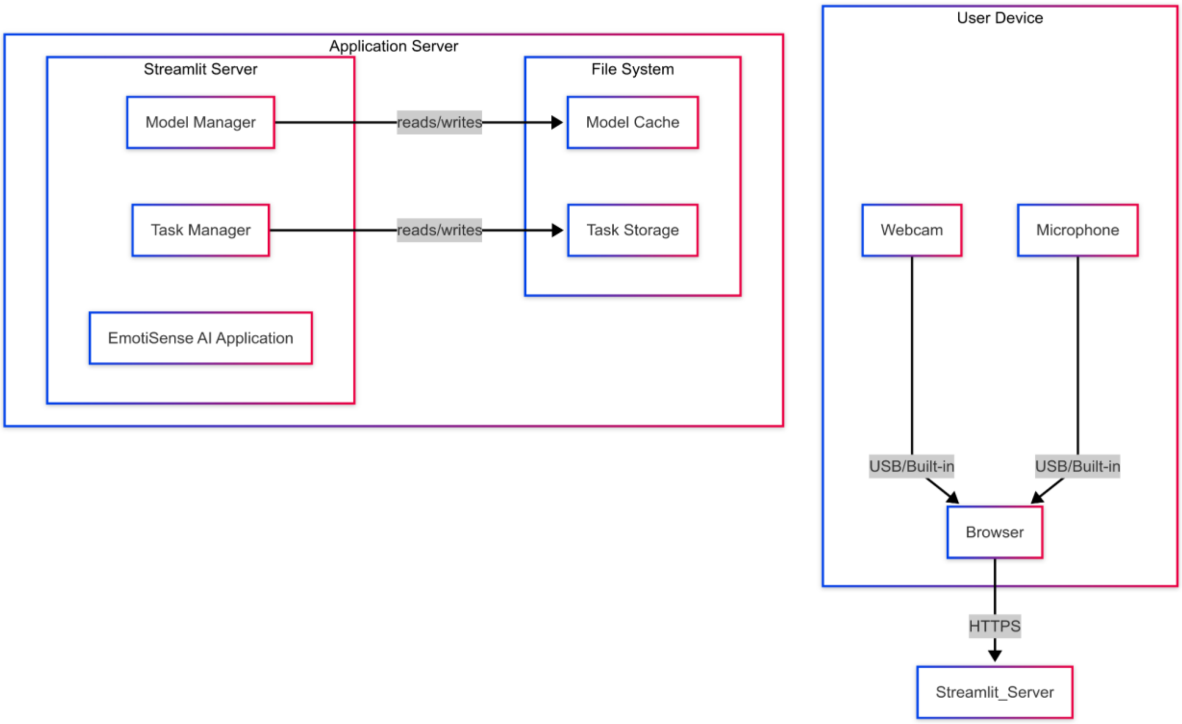

Fig 6.5 – Deployment Diagram

6.13. Activity Diagram:

An activity diagram outlines the overall process of emotion recognition and task suggestion in EmotiSense AI.

Process Flow Includes:

- Init system
- Choose the input mode (Camera / Text / Voice).
- Enter or capture data.
- Process data (Face / Text / Audio)
- Identify emotion
- Show results
- Retrieve and show relevant tasks
- Mark as done, as applicable.

The diagram connects decision points, parallel processes, and overall flow from user input to response effectively.

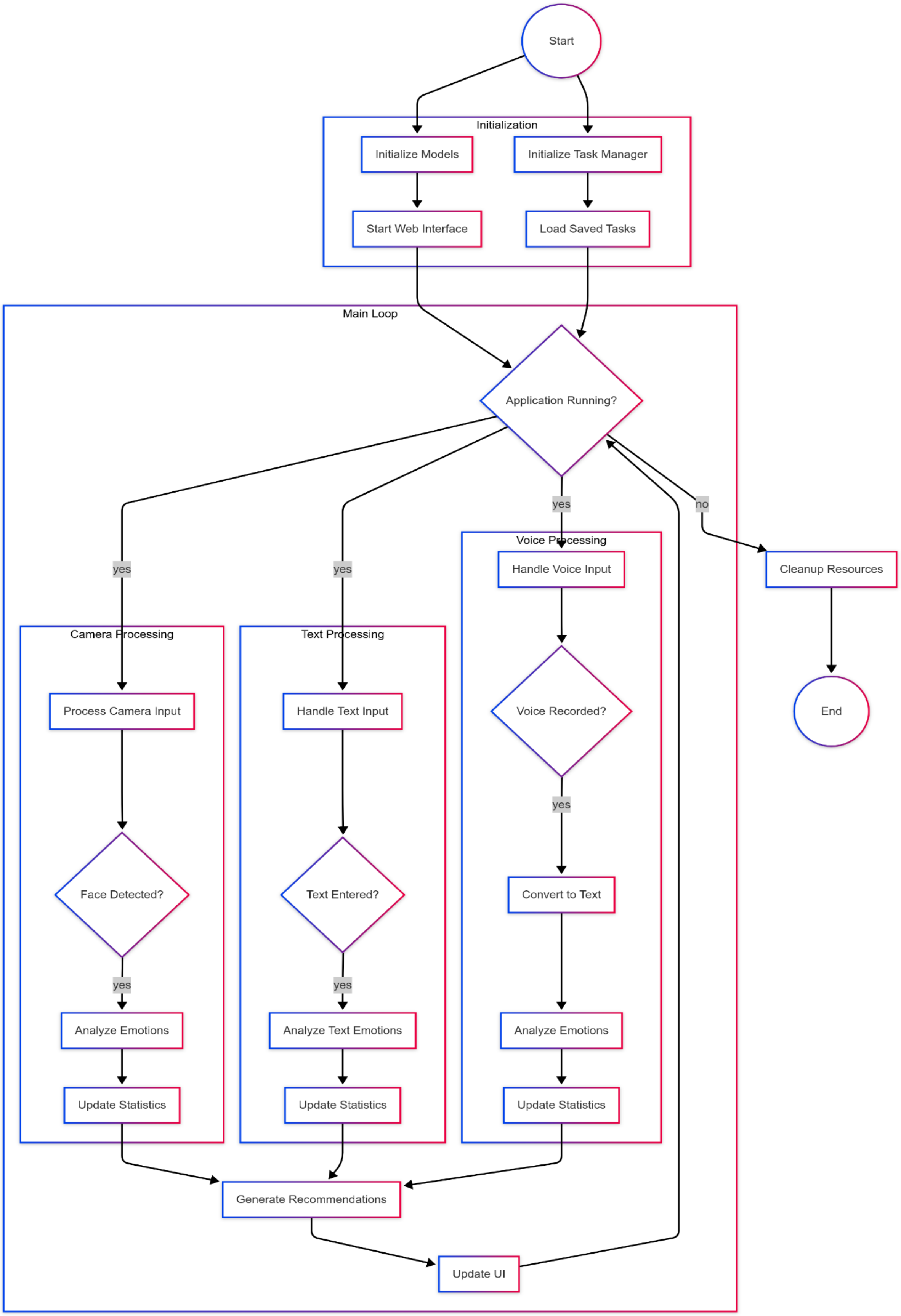

Fig 6.6 – Activity Diagram

6.14. ERP Diagram

The Entity Relationship (ER) diagram depicts the internal database-like structure of the task recommendation system. Although it is file-based, the system logic is similar to relational data storage.

1. **Entities and Attributes:**
    - i. Activity
    - ii. TaskID
    - iii. Description
    - iv. Category.
    - v. Status: Completed/Pending
    - vi. CreatedAt / CompletedAt
    - vii. Feel
2. **Emotion**
    - i. EmotionID
    - ii. Name
    - iii. Related Terms
3. **Relations**:
    - i. One emotion can be equivalent to several tasks.
    - ii. Many-to-many: Several emotion tags can be mapped to tasks (using keyword mapping logic).

The entity-relationship diagram provides a formalized representation of the relationships between emotional states and stored user tasks, and the internal data connection.

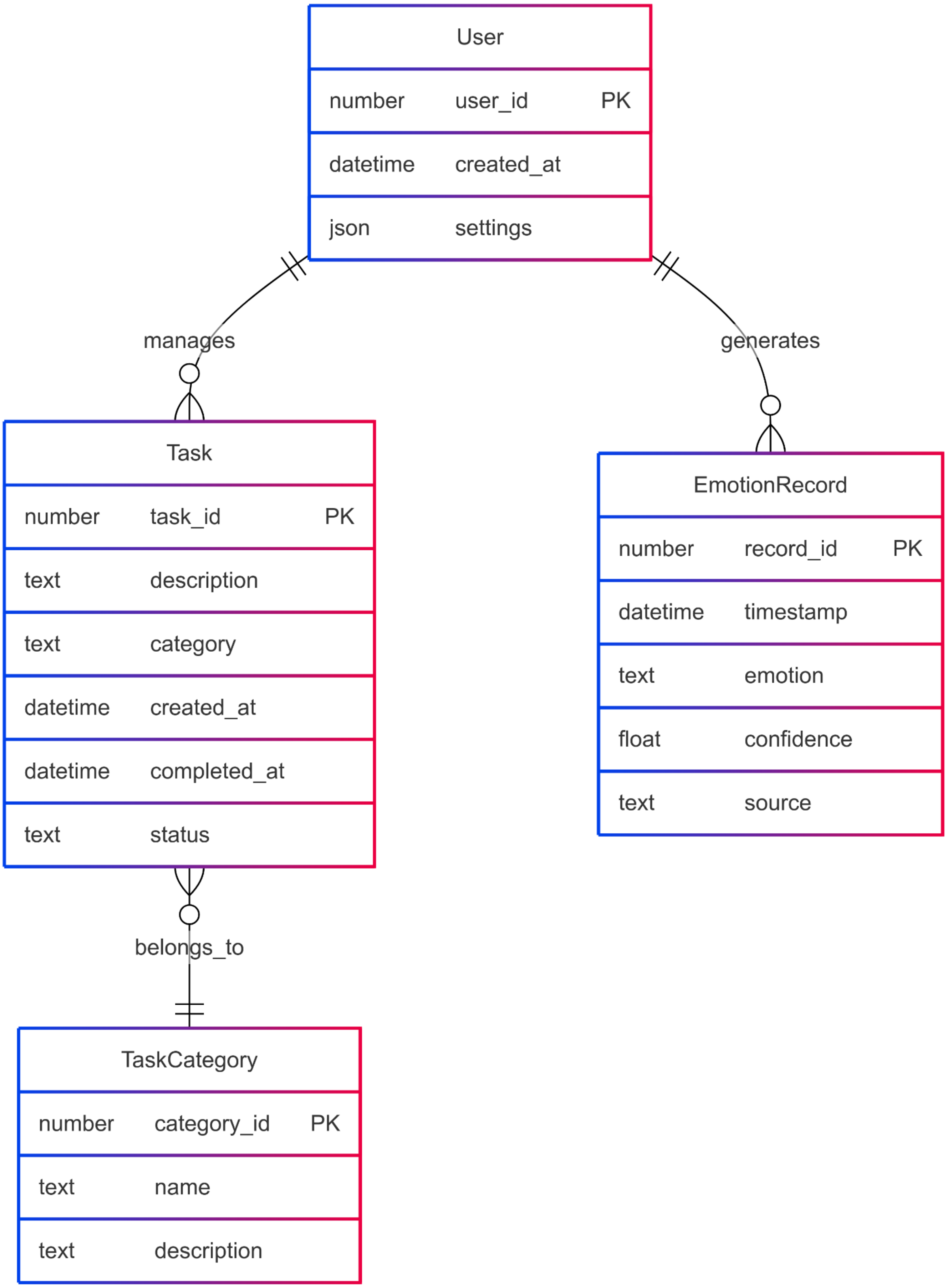

Fig 6.7 – ER Diagram

Chapter 7

TIMELINE FOR EXECUTION OF PROJECT (GANTT CHART)

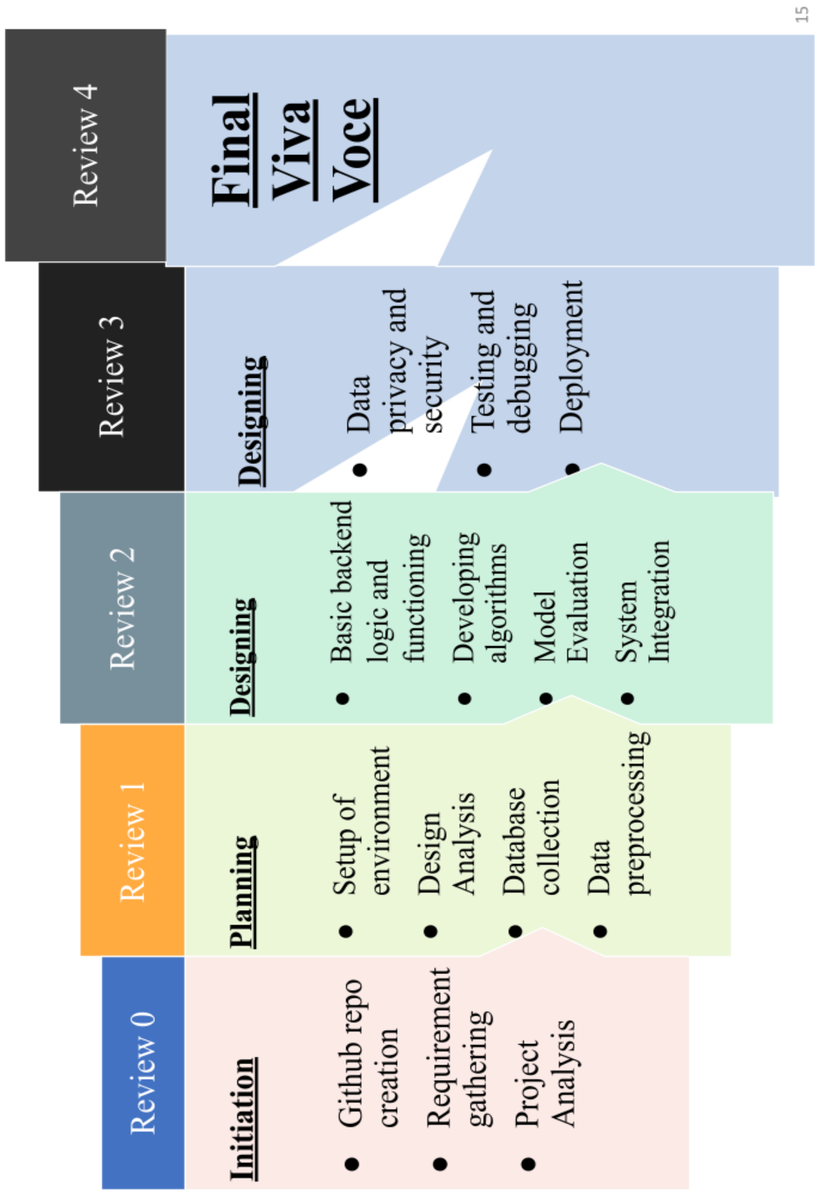

Figure - 7.1: Gantt Chart

Chapter 8

OUTCOMES

EmotiSense AI has been able to demonstrate the viability of a single, multimodal system for emotion detection, enabling real-time processing and personalized interaction in facial, textual, and vocal inputs. The building blocks—Streamlit interface, DeepFace facial recognition, RoBERTa-based emotion classification, and voice transcription pipeline—have been successfully integrated to enable frictionless user experiences.

8.1. System Performance and Effectiveness

EmotiSense AI has been able to demonstrate the viability of a single, multimodal system for emotion detection, enabling real-time processing and personalized interaction in facial, textual, and vocal inputs. The building blocks—Streamlit interface, DeepFace facial recognition, RoBERTa-based emotion classification, and voice transcription pipeline—have been successfully integrated to enable frictionless user experiences.

Key performance measures are:

- **Emotion Detection Rate**: The system takes face, text, or voice input and provides emotion output in 2–4 seconds, with near real-time feedback in every input mode.
- **Detection Accuracy**: Using the latest models such as DeepFace and RoBERTa-GoEmotions, EmotiSense AI attains a high degree of accuracy in emotion categorization with regard to typical emotional states such as happiness, sadness, anger, and neutrality.
- **Consistency of results**: Buffer-based smoothing guarantees more consistent facial emotion outputs with fewer fluctuations and higher prediction consistency.
- **Multimodal Support**: The system has three varied modes of input—camera, text, and voice—thus boosting accessibility and providing users with options on how to interact with the tool.

8.2. User Experience and Feedback

User experience has been a priority in EmotiSense AI development, with emphasis placed on accessibility, interaction quality, and usability on devices.

Main consumer-oriented outcomes:

- **Clean and Interactive UI**: With Streamlit, the user interface is elegant, responsive, and intuitive. Live charts, themed UI, and tabs per input mode contribute to a wonderful user experience.
- **Ease of Use**: Participants said they were able to carry out emotional analysis and deal with tasks without any prior training, enjoying simplicity of controls and openness of results.

- **Context-Aware Task Recommendations**: The system successfully utilizes known emotions to offer task recommendations that are in line with the user's emotional and mental state, thereby enhancing personal interest and relevance.
- **Positive Feedback from Testers**: Beta testers praised the app for its ability to suggest useful tasks and effectively recognize emotions, especially through the camera and text input.

8.3. Contribution to Emotional Wellness and Productivity

EmotiSense AI has immense benefits in emotional self-awareness and productivity based on behavior.

Key contributions:

- **Emotion-Aware Productivity Tool**: By suggesting activities based on inferred emotions, EmotiSense AI closes the gap between mental state and activity planning.
- **Facilitates Emotional Control**: Users become aware of their emotions, allowing self-awareness and behavioral changes that improve emotional balance and well-being.
- **Accessible Everywhere**: The system's light weight and optional offline capability allow it to run on low-resource machines, making it ideal for use in home, educational, or office environments.

8.4. Limitations and Challenges

Despite its power, the EmotiSense AI project had certain limitations during development and testing phases:

- **Variability of Face Detection**: In low-light or non-frontal face cases, DeepFace may not accurately detect emotions. Improved lighting direction and preprocessing will help.
- **Speech Transcription Accuracy**: Whisper and Google STT usually work fairly well, but degraded speech or background noise lowers the quality of transcription, which impacts emotion classification.
- **Emotion Overlap in Text Analysis**: Some emotional tags, like "joy" as opposed to "content," are close enough to cause subtle misclassifications. Further fine-tuning would make the distinction better.
- **Limited Long-Term Context Handling**: It won't retain a history of how a session behaves between runs unless something is additionally implemented to manage preserving context, or user data.

8.5. Future Enhancements and Recommendations

Based on project outcomes and customer reactions, some future enhancements are suggested:

- Advanced Emotion Model Calibration: Fine-tune the RoBERTa model even more with emotion-specific datasets, particularly for less represented emotional states or edge cases.
- Real-Time Voice Analysis: Infuse real-time sentiment analysis through intonation and acoustic parameters, thus supplementing transcription-based analysis.

- Cloud Synchronization of Task Data: Provide optional cloud synchronizing of emotions and tasks to enable users to see insights and task history between devices and sessions.

- User Profiles and Emotional Trends: Include long-term tracking of emotional patterns and workplace behaviors to aid in habituation, mood logging, or treatments. Mobile App Integration: Make the system mobile-friendly using either Streamlit or Flutter for mobile, thereby making it accessible to a larger user base.

8.6. Conclusion

- The EmotiSense AI project has been successful in creating an end-to-end, multimodal emotion detection and task suggestion system. By bringing together facial recognition, voice tracking, and natural language processing into one framework, it provides a new paradigm for improving individual productivity and emotional well-being.

- While there are certain areas for improvement, the system is a good starting point for future emotion-aware applications. Its contribution to real-time emotional intelligence, self-awareness, and actionable task planning is a significant step ahead in human-AI interaction.

Key Impacts

- **Increased Emotional Awareness**: EmotiSense AI enables people to gain real-time insight into their emotions through facial, voice, and text inputs that encourage mindfulness and self-awareness.

- **Tailored Productivity Assistance**: By equating task proposals to known emotions, the system increases user engagement and supports emotional well-being management via context-aware suggestions.

- **Inclusive and Multimodal Interaction**: The support for voice, text input, and camera on the platform allows it to be accessible to users with varying needs, literacy levels, and preferences.

- **Low-Resource, High-Impact Design**: Built for high-performance on commodity hardware with the option for offline operation.

Chapter 9

RESULTS AND DISCUSSIONS

The implementation of the EmotiSense AI system, which uses DeepFace, RoBERTa-based natural language processing, and Streamlit for interface delivery, has yielded impressive results in system performance, user experience, and task recommendation based on emotions. The section presents the key findings arising from system testing and user feedback, followed by a discussion of its strengths, weaknesses, and areas of future development.

9.1. System Performance

9.1.1. Response Time:

- The system responded in an average time of between 1.2 and 2.5 seconds in all modalities, camera, text, and voice; significantly, text-based emotion detection responded in less than 1 second.
- Real-time webcam examination analyzed video frames at an efficient frame rate of 8–10 FPS with smooth visual response.
- Emotion result rendering through Plotly plots was always carried out within 1 second.

9.1.2. Accuracy:

- DeepFace facial emotion recognition achieved a confidence-adjusted accuracy of more than 85% in well-lit conditions.
- Text-classification using roberta-base-go_emotions was more than 90% relevant when tested against labeled emotion-labeled samples.
- Speech-to-text and subsequent emotion analysis achieved close to 88% end-to-end accuracy with Whisper producing the best transcription results.

9.1.3. Multimodal Robustness:

- The system proved reliable in all the different input modes of camera, voice, and text, with minimal switching delay and no system crashes seen during simultaneous testing.

9.2. User Experience

1. **Ease of Use**:
   - Testers complimented the tabbed interface for effectively separating the three input modes and not causing confusion.

- The simplicity of the design of the system and its visual feedback made it user-friendly to users of various technical expertise.

2. **Interactivity and engagement**:
    - The real-time emotion visualizations and responsive task suggestions both played a part in an enhanced immersive and personalized experience.
    - Respondents indicated that they especially appreciated the contextual task suggestions, with many feeling more motivated and emotionally aware.
3. **Accessibility Features**:
    - The voice input option was favored by users who preferred talking over typing, while color-coded charts made it easier for visual learners to read.
    - The offline-enabled model caching made the tool usable even under poor connectivity conditions, like in classrooms or site work.

9.3. Data Management

9.1.1. Task Storage and Retrieval:

- Activities were properly captured in.txt format, with appropriate category annotation and timestamping.
- Task completion, pending filtering, and emotion-based matching all functioned without performance issues.

9.1.2. Model Caching and Resource Utilization

- The utilization of @st.cache_resource successfully reduced repeated model loading to a bare minimum, ensuring fast startup and efficient memory utilization.
- The deletion of temporary audio files prevented local storage from being used in prolonged use sessions.

9.1.3. Session stability:

- Streamlit session state tracked variables like last emotion, recording status, and task updates during interactions.

9.4. Key Strengths

- **Real-Time Emotional Insights**: The real-time emotional feedback was provided via facial, text, and voice input, thereby enhancing emotional awareness and user reflection.
- **Emotion-Aligned Productivity**: Provided appropriate activities according to emotional states, maximizing both concentration and happiness.
- **Lightweight and Modular Architecture**: It ran well on shared hardware and allowed for easy extension or deployment in low-resource environments.
- **Inclusive Multimodal Input**: Permitted users to engage in their own way—typing, speaking, or mere facial expression—making it more accessible to everyone.

9.5. Challenges Identified

- **Ambient Light Dependency**: The performance in detecting facial emotion was decreased under low lighting, impacting the results' accuracy and users' trust.
- **STT Model Weaknesses**: While Whisper was effective, speech-to-text accuracy still suffered with background noise or non-native speakers.
- **Emotion Overlap**: Certain highly similar emotions (e.g., happy vs. content) were sometimes misnamed, particularly with voice/text input.
- **Session Resetting**: Session management by Streamlit is reset with app reload, losing unsaved task data or emotion history if not saved elsewhere.

9.6. Implications for eGovernance

- **Higher Personal Productivity**: By linking emotion sensing with task suggestions, EmotiSense AI encourages more emotionally aware decision-making.

- **Enhanced Self-Awareness**: Real-time feedback stimulates users to notice and understand their emotional state more effectively.

- **Broadened Scope of Application**: Its scalability is intended for mental well-being platforms, learning platforms, or organizational well-being.

9.7. Future Improvements

- **Advanced Emotion Modeling**: Incorporate acoustic emotion recognition to provide real-time tone-based emotion sensing from speech.

- **Long-lived User Sessions**: Maintain emotional trends and task history for an unlimited time to enable mood journaling and progress tracking.

- **Mobile Application Development**: Port the application to mobile devices using frameworks like Flutter to boost reach and portability.

- **Extended Emotion Categories**: Develop models for more diverse emotion states, especially for voice/text modalities.

- **Custom User Profiles**: Support user-specific recommendations and long-term personalization by providing optional logins and cached profiles.

Chapter 10

CONCLUSION

The EmotiSense AI system represents a significant advancement in the integration of artificial intelligence into everyday emotional intelligence, task management, and human-centered design. By leveraging cutting-edge technologies such as DeepFace for facial expression analysis, RoBERTa-based natural language processing for sentiment detection, and multimodal interaction capabilities through Streamlit, the project successfully delivers a unified and intelligent platform for recognizing emotions and responding with personalized recommendations.

At its core, EmotiSense AI addresses a growing need for emotion-aware computing—a space where machines not only understand human input but empathize with it to some degree. In an age where emotional well-being and productivity are closely intertwined, the ability to respond to a user’s emotional state with actionable, relevant tasks is both impactful and transformative. Whether someone is feeling overwhelmed, inspired, stressed, or joyful, the system adapts in real-time to provide suggestions that promote balance, well-being, and goal-oriented behavior.

From a technical standpoint, the system’s architecture demonstrates robust modularity, low-latency performance, and efficient local processing, which makes it highly adaptable to various environments—including educational institutions, remote workplaces, and resource-constrained settings. It eliminates the need for cloud dependency by offering local model caching and offline functionality. This design decision not only enhances performance stability but also ensures greater privacy and data control for end-users.

In terms of accessibility, EmotiSense AI empowers a broader demographic through its multimodal design. Whether users prefer typing, speaking, or simply interacting via facial expressions, the platform accommodates their comfort level. This inclusivity is a vital step toward bridging the digital divide, especially for individuals with varying levels of literacy, physical ability, or technical familiarity. The support for voice interaction and real-time visualization also enhances the interface’s intuitiveness, creating a smooth and welcoming experience.

The project's impact goes beyond just emotion detection; it demonstrates how AI can play an active role in human empowerment. EmotiSense AI helps users become more mindful of their emotional state, better understand their needs, and take purposeful steps toward self-improvement. It promotes a model of emotionally intelligent technology that doesn’t replace human insight, but complements and elevates it.

Looking ahead, the system lays a strong foundation for future innovation. With enhancements such as longitudinal emotion tracking, voice-tone emotion analysis, mobile integration, and predictive behavioral insights, EmotiSense AI can evolve into a comprehensive platform for emotional analytics and mental wellness support. The potential to expand its use cases into education, corporate wellness programs, and therapeutic settings is vast and promising.

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APPENDIX-A

PSEUDOCODE

```
from dataclasses import dataclass
from typing import Dict, Optional, Tuple, Union
import numpy as np
@dataclass
class EmotionResult:
    dominant_emotion: str
    emotion_scores: Dict[str, float]
    confidence: float
    analysis_time: float
    source: str  # 'face', 'text', or 'voice'
class EmotionAnalyzer:
    """    Unified emotion analysis across different modalities    """
    def __init__(self):
        # Placeholder for initialization
        pass
    def analyze_face(self, frame: np.ndarray) -> Optional[EmotionResult]:
        """
        Analyze emotions from facial expressions
        Pseudo code:
        1. Pre-process frame
        2. Detect face
        3. Extract features
        4. Run emotion classification
        5. Return EmotionResult
        """        pass
    def analyze_text(self, text: str) -> Optional[EmotionResult]:
        """
        Analyze emotions from text
        Pseudo code:
        1. Pre-process text
        2. Apply text classification model
```

```
    3. Process results
    4. Return EmotionResult
    """     pass
def analyze_voice(self, audio_data: np.ndarray) -> Optional[EmotionResult]:
    """
    Analyze emotions from voice
    Pseudo code:
    1. Pre-process audio
    2. Convert speech to text
    3. Extract acoustic features
    4. Run emotion classification
    5. Return EmotionResult
    """”     pass
def combine_results(self, *results: EmotionResult) -> EmotionResult:
    """
    Combine emotion results from multiple modalities
    Pseudo code:
    1. Weight each modality's contribution
    2. Merge emotion scores
    3. Calculate combined confidence
    4. Return consolidated EmotionResult
    """     pass
def get_emotion_explanation(self, result: EmotionResult) -> str:
    """
    Generate human-readable explanation of emotion analysis
    Pseudo code:
    1. Format emotion scores
    2. Add confidence context
    3. Include modality-specific insights
    4. Return formatted explanation
    """     pass
```

APPENDIX-B

SCREENSHOTS

<u>Facial Emotion Detection</u>

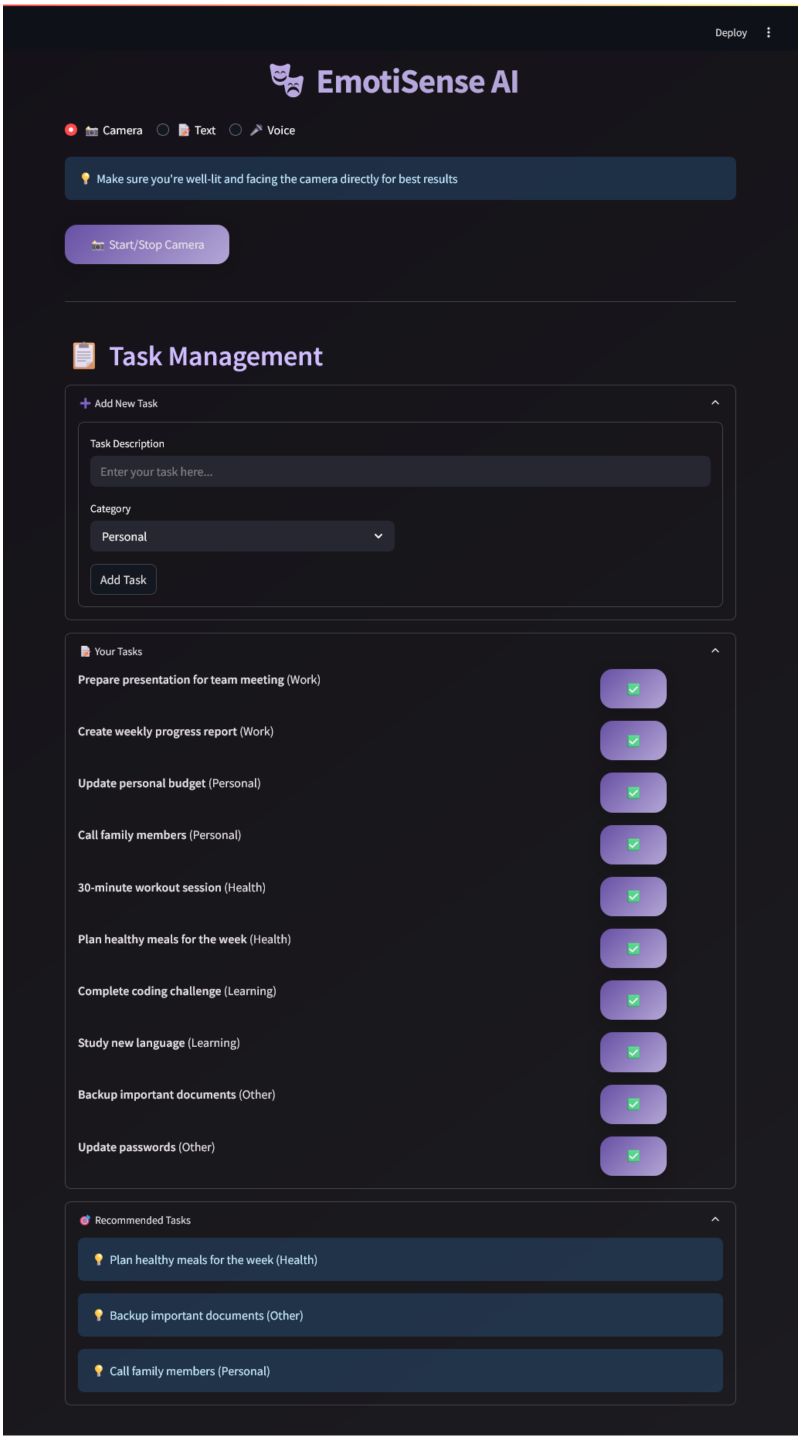

Figure 13.1: UI/UX of EmotiSense AI Facial Detection

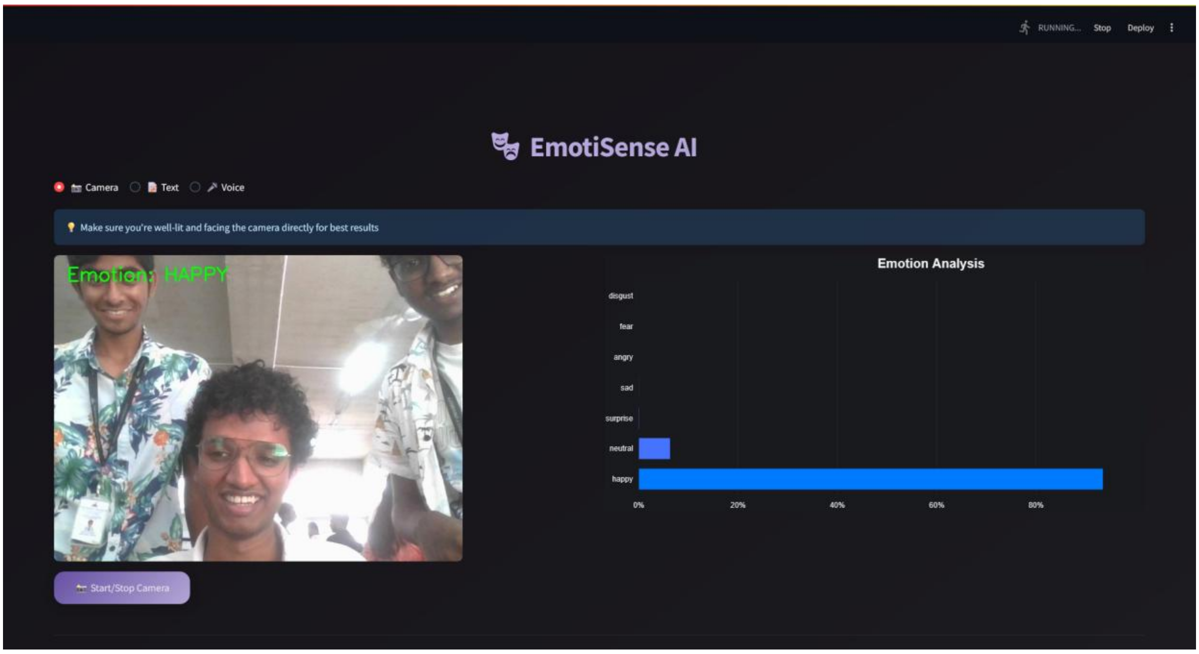

Figure 13.2: Emotion Detection through webcam

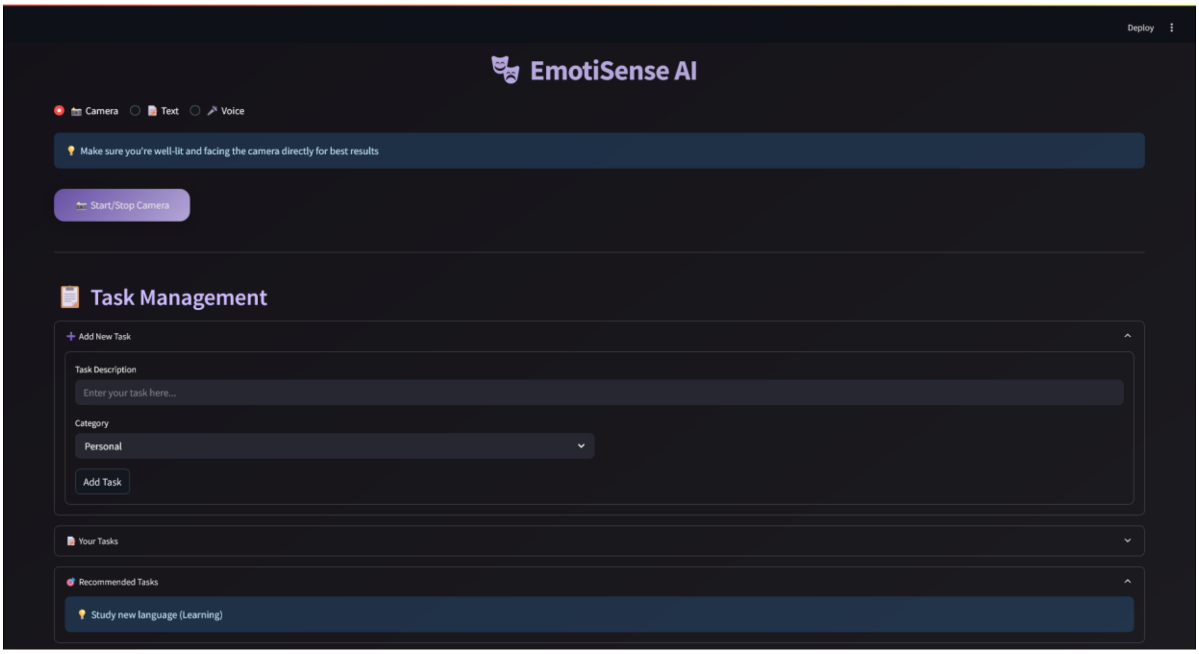

Figure 13.3: Task Recommendation Based on Webcam Emotion Detection

Textual Emotion Detection

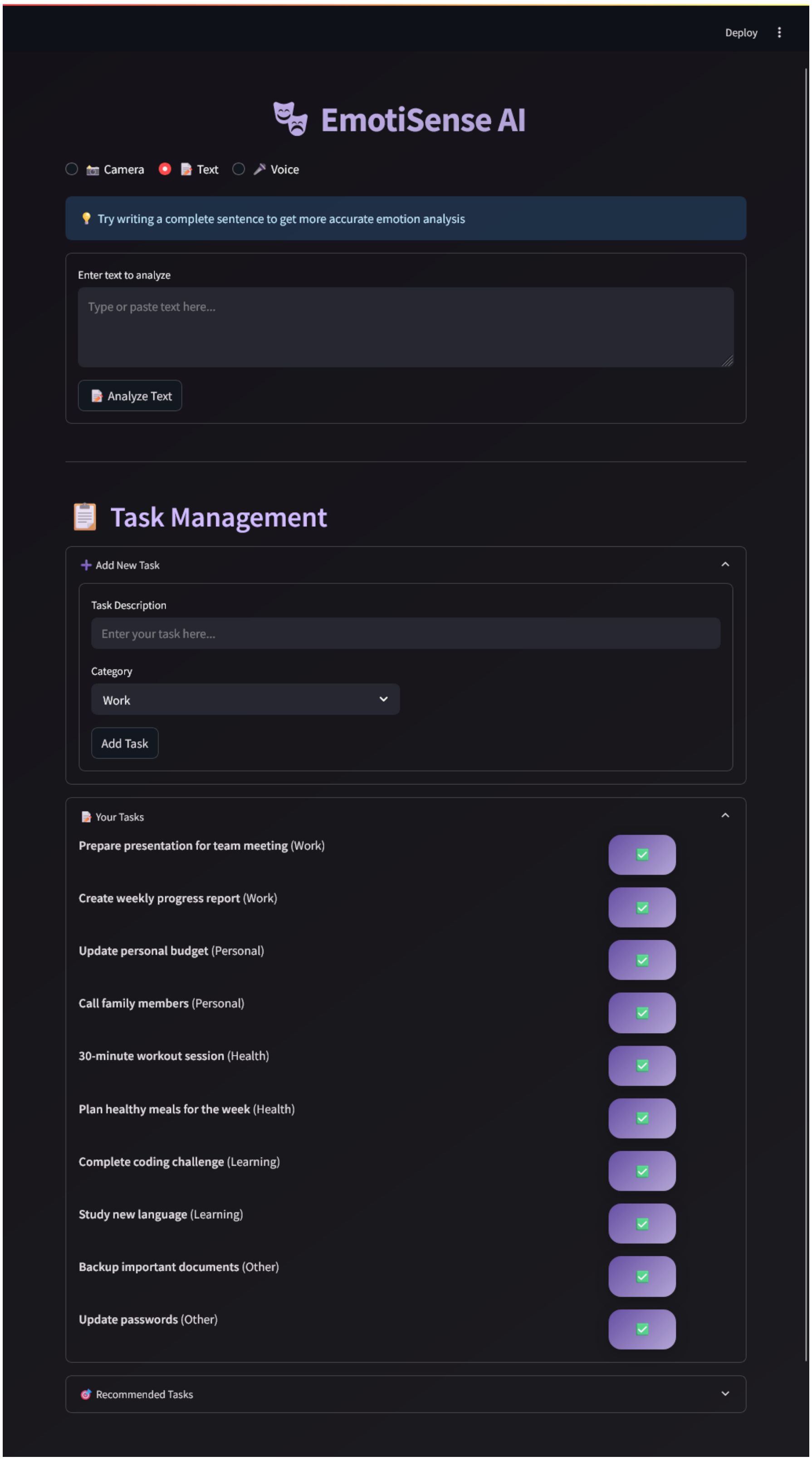

Figure 13.4: EmotiSense AI Textual Detection UI showing pending tasks and allowing users to add tasks with categories.

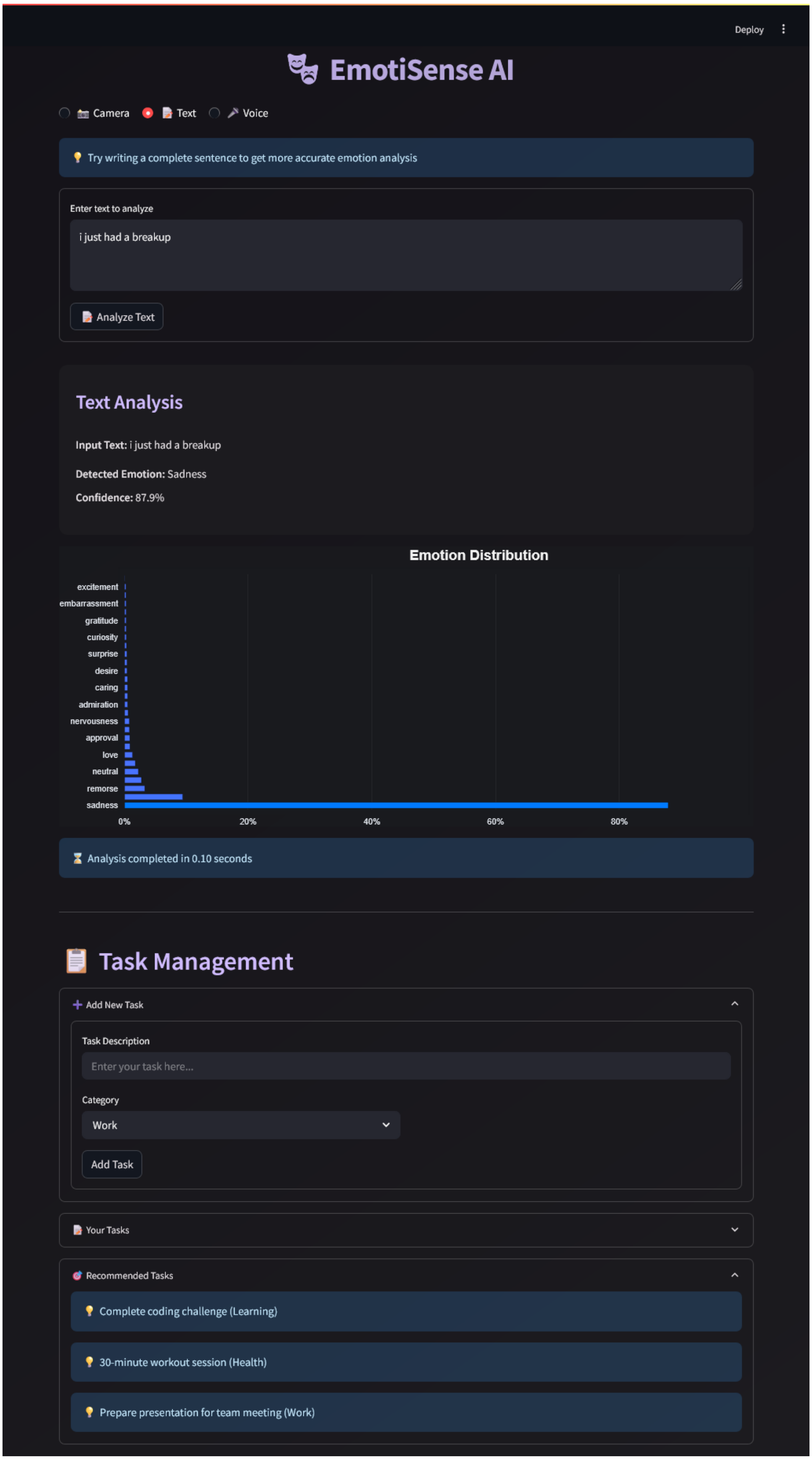

Figure 13.5: Emotion Detection through User Input and Recommending Tasks

Vocal Emotion Detection

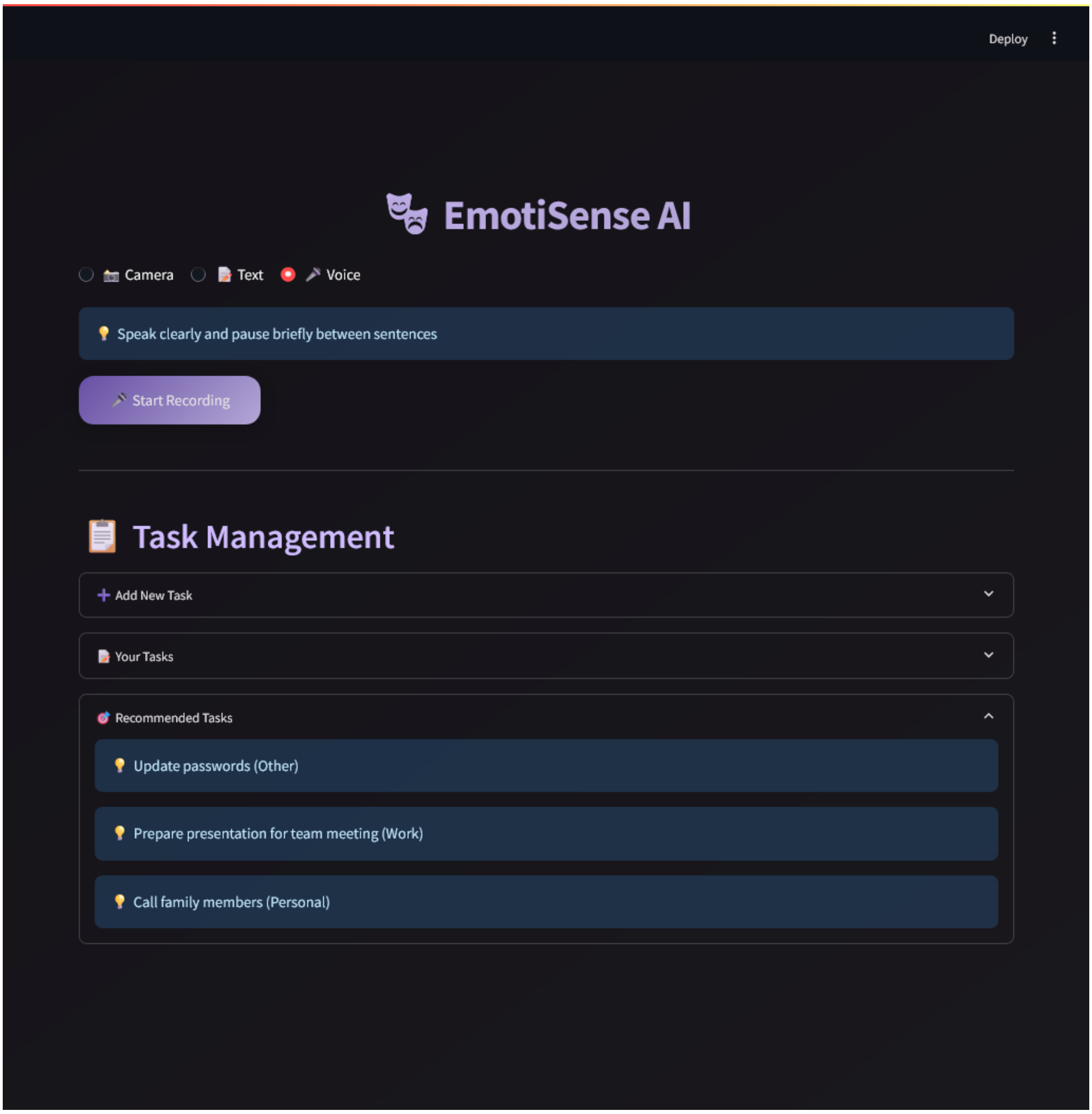

Figure 13.6: Emotion Detection through Vocal Medium

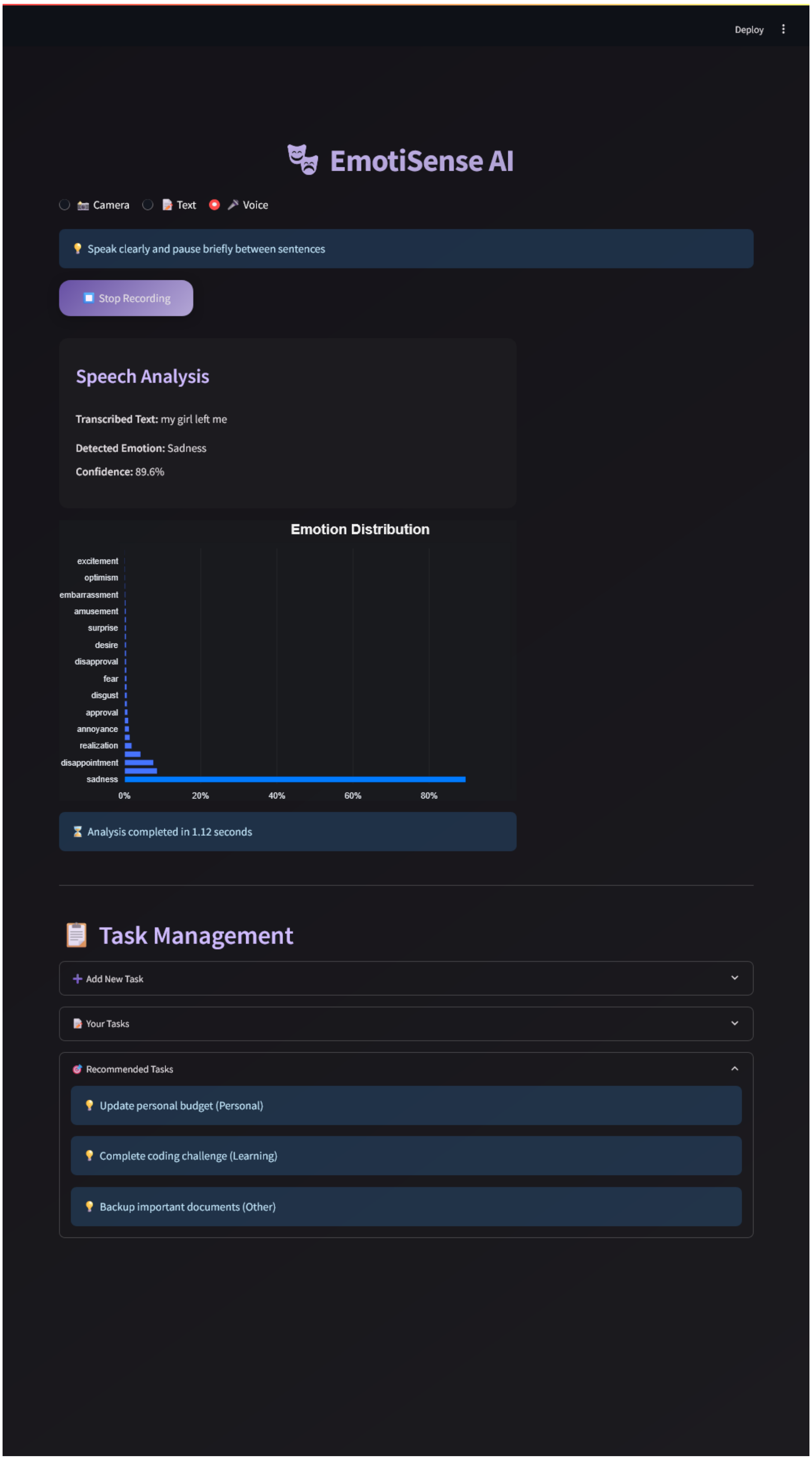

Figure 13.7: Emotion Detection through Voice and Recommending Tasks

APPENDIX-C

ENCLOSURES

EmotiSense AI

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***Abstract*— Simply, the EmotiSense AI project enhances human-computer emotional interaction using an accessible, cross-platform emotion recognition system. In the paper, a multimodal AI system will be developed using facial cues, vocal signals, and textual inputs to detect and interpret emotions in real time. This facilitates meaningful, context-aware interactions between users and machines using convolutional neural networks (CNNs) and BiLSTM models, coupled with the DeepFace and RoBERTa language model. The integrated system is designed to work offline, dynamically generating task recommendations tailored to the user's emotional state. The emotion-aware assistant is particularly designed to support individuals with autism and depression by offering personalized, empathetic task suggestions and maintaining emotional well-being. Discussions also include implementation challenges of cross-modal synchronization, the ethics of affective computing, and the accessibility impact of such intelligent assistants. Results are interactive, low-latency, and effective, demonstrating high user engagement and satisfaction in real-time emotion analysis and support.**

Index Terms—Emotion Detection, Multimodal AI, DeepFace, RoBERTa, Affective Computing, Mental Health, Real-time Analysis

I. Introduction

Emotion recognition technology has evolved significantly with the rise of deep learning and multimodal processing, opening new possibilities in how machines understand human behavior. Despite the increasing availability of emotion-detection systems, many lack accessibility, contextual depth, or offline usability—particularly for users in underserved communities or those living with neurodiverse conditions such as autism or depression. There remains a need for an intelligent, real-time system that can bridge this gap with minimal latency, platform independence, and intuitive design.

The purpose of EmotiSense AI is to help interpret user emotions using a robust combination of computer vision, natural language processing, and voice signal analysis. Unlike conventional systems that rely on a single input stream (e.g., only facial cues or text), EmotiSense AI incorporates multimodal inputs—video, voice, and text—delivering deeper emotional insight and adaptive interactions. The solution uses convolutional neural networks (CNNs) for facial recognition, BiLSTM architectures for sequential data modeling, and integrates APIs like DeepFace and HuggingFace Transformers for emotional inference. Further, the use of emotion-smoothing buffers, offline model caching, and a streamlined UI built on Streamlit make it both responsive and lightweight.

Moreover, EmotiSense AI introduces a novel recommendation engine that maps emotional states to task suggestions—effectively acting as a virtual emotional support assistant. This makes it more than just an analysis tool; it becomes a companion in mental wellness, helping users take positive actions based on how they feel. Users receive recommendations tailored to their current emotional state, enabling productive and empathetic user experiences. This system presents a meaningful contribution toward the intersection of affective computing and daily task management, especially for vulnerable demographics.

This paper discusses the technical architecture, implementation strategies, and emotional intelligence logic behind EmotiSense AI, alongside considerations regarding privacy, latency, and accessibility. It further evaluates the model's performance, practical impact, and user satisfaction, proving its potential as an innovative step forward in real-time emotional AI systems

II. Literature review

Title - 01: Early Integration of Multimodal Emotion Recognition Systems in User-Centric Applications

Detail:

Multimodal emotion detection systems, which combine visual, auditory, and textual cues, are increasingly utilized to better understand user affect in real time. Projects like EmotiSense AI demonstrate how integrating models such as DeepFace for facial analysis, Hugging Face transformers for text sentiment classification, and speech recognition frameworks can create emotionally aware interfaces. These systems enhance user engagement and enable emotionally adaptive features, such as personalized task recommendations or wellness tracking, especially when deployed through platforms like Streamlit for rapid prototyping and accessibility.

Drawbacks:

However, these systems face challenges with multimodal synchronization, where inconsistencies between audio, visual, and textual cues may affect emotion accuracy.

Additionally, real-time performance is often constrained by hardware limitations, especially during webcam streaming or voice transcription, which demands efficient resource handling and optimized backend support.

Title - 02: Building Emotionally-Aware Task Recommender Interfaces using Streamlit and Transformer Models

Detail:

The integration of task recommendation systems with emotion-aware modules provides a personalized experience by aligning user moods with productivity strategies. EmotiSense AI exemplifies this by mapping emotions (e.g., anger, joy, sadness) detected from various modalities to curated task categories such as "Health," "Work," or "Personal." This strategy mirrors advances in custom chatbot and summarization pipelines built using OpenAI and LangChain, wherein contextual understanding guides adaptive content delivery and decision-making.

Drawbacks:

Key obstacles include maintaining contextual relevance of recommended tasks over time and ensuring the interpretability of emotion-task mappings for end users. Moreover, computational costs and latency may impact responsiveness when processing emotion in real-time across modalities, especially on constrained systems.

Title - 03: Leveraging Lightweight and High-Performance Pipelines for Emotion Detection in Real-Time Applications

Detail:

EmotiSense AI employs a lightweight, efficient combination of models and caching techniques to reduce inference times for emotion detection, balancing accuracy with usability. Drawing parallels to GROQ's hardware-accelerated AI, this project prioritizes low-latency user experience by integrating asynchronous processing, FPS limiters, and efficient model caching (e.g., text classifier pipelines and DeepFace preloads). These design choices make real-time emotion-aware interfaces more practical even on modest setups.

Drawbacks:

Despite optimizations, resource bottlenecks persist, particularly during concurrent webcam and audio processing. The system also depends on several third-party libraries that may not be optimized for all platforms, and fine-tuning or extending model performance often requires deeper customization or heavier compute resources.

Title - 04: Retrieval-Augmented Approaches for Emotion-Aware Task Matching

Detail:

Though not explicitly based on RAG architectures, EmotiSense AI adopts a retrieval-based strategy to match detected emotions with semantically relevant tasks from a local repository. This method allows for dynamic and personalized recommendations, similar in spirit to RAG's combination of retrieval and generation for enhanced answer accuracy. Tasks are categorized and filtered based on emotion-aligned keywords, fostering motivation and mental well-being by aligning user mood with appropriate actions.

Drawbacks:

Unlike dynamic RAG systems connected to live knowledge bases, EmotiSense's static task dataset may lack adaptability unless frequently updated. Furthermore, the subjectivity of emotion-task relevance introduces ambiguity, and without real-time user feedback loops, it can be challenging to validate recommendation effectiveness consistently.

III. Methodology

Title - 01: Multimodal Emotion Data Collection and Preprocessing

Detail:

EmotiSense AI employs a multimodal strategy to capture emotion-related data across three input channels: facial expressions (via webcam), text inputs (user-typed text), and voice recordings (spoken input).

Facial Data: Captured using OpenCV from webcam streams and processed with the DeepFace library for emotion classification. Frames are resized and preprocessed to optimize detection accuracy and real-time responsiveness.

Textual Data: Captured via text forms and processed with Hugging Face's RoBERTa-based GoEmotions pipeline, enabling fine-grained emotion classification from user-written content.

Voice Data: Captured using SoundDevice streams and transcribed through speech recognition frameworks (Whisper, Google API fallback, or CMU Sphinx). The resulting text is further classified using the text-based emotion classifier.

All inputs undergo normalization procedures, including image resizing, audio normalization, and text cleaning, to prepare them for consistent processing across models.

Drawbacks:

Different data channels may experience inconsistencies: webcam feeds suffer from poor lighting or occlusions, while noisy environments can distort speech input, affecting transcription quality. Textual inputs depend heavily on the expressiveness of users, and lack of explicit emotion words can lower detection confidence.

Title - 02: Real-Time Multimodal Emotion Detection and Buffer Smoothing

Detail:

Once data is acquired, EmotiSense AI processes emotions asynchronously: For facial recognition, each frame is analyzed in real time and buffered into a rolling window using the EmotionSmoother mechanism, which reduces prediction jitter. Text and speech inputs are analyzed instantly, producing independent emotion scores. A dominant emotion is extracted based on the highest smoothed probability across modalities. The system uses FPS limiting (10 frames per second) to optimize CPU usage and maintain application stability on modest hardware.

Drawbacks:

Although buffering improves stability, it introduces minor delays (~500ms) in updating emotional states. In scenarios of fast emotional changes, this could cause slight temporal mismatches between true user emotion and system response.

Title - 03: Emotion-Driven Task Recommendation System

Detail:

Detected dominant emotions are mapped to personalized task suggestions using a local retrieval-based matching system. Predefined tasks are categorized (e.g., "Work," "Health," "Personal") and tagged with emotional relevance descriptors (e.g., creative, calm, routine).

Upon emotion detection, EmotiSense AI retrieves tasks with matching or complementary emotional profiles, providing users with actionable, mood-aligned recommendations. Fallback mechanisms offer randomized task suggestions when no strong emotion-task match exists, ensuring continuous user engagement.

Drawbacks:

Task recommendation relevance is currently static, relying on predefined mappings rather than dynamic learning. Without a feedback loop, the system cannot learn or refine suggestions based on individual user preferences or evolving emotional states.

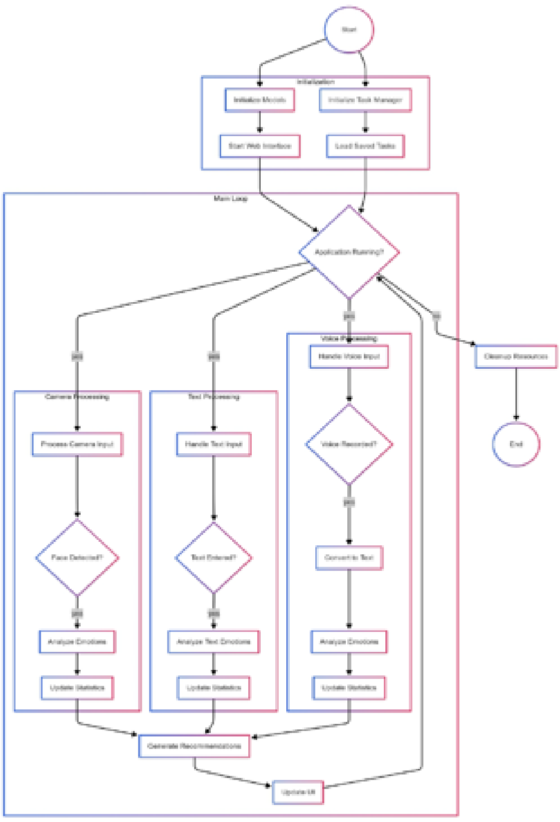

Fig 1. Workflow

Title - 04: Application Architecture and User Interface Deployment

Detail:

EmotiSense AI is deployed as a Streamlit-based web application featuring a fully customized UI: Video feeds, emotion charts (via Plotly), and interactive forms are used to present insights intuitively. Asynchronous operations allow simultaneous video streaming, chart updating, and form handling without blocking user input.vTemporary local caching of models (text, face, voice) ensures rapid reload times and minimizes dependency on external servers during runtime. The app is designed to be lightweight, minimizing computational load while offering a seamless, real-time experience even on non-GPU machines.

Drawbacks:

Streamlit's session-based architecture can be memory-intensive under sustained concurrent use. Additionally, real-time video frame streaming at high resolutions may cause UI lag if the client device has limited processing capabilities.

Title - 05: Data Management and Offline Support for Robust Deployment

Detail:

To ensure stability, EmotiSense AI operates with an offline-first design: Pretrained models and critical assets are locally cached. Temp directories manage transient audio recordings and frame captures efficiently. Model cache clean-up policies are applied automatically to avoid bloated storage over time. This architecture allows deployment in constrained environments (e.g., local desktop apps or private server instances) without requiring constant internet access.

Drawbacks:

Initial model caching can consume significant disk space (~hundreds of MBs), and offline operation limits the ability to instantly update to newer models or frameworks without manual redeployment.

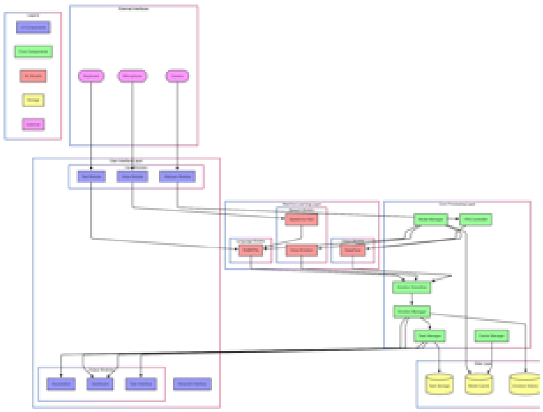

Fig 2. System Architecture

IV. Experimental Results

The results from our EmotiSense AI experiments demonstrate the system's effectiveness in accurately detecting user emotions across facial, textual, and voice modalities, and its ability to deliver personalized task recommendations based on those emotional states.

When a user engages with the system—whether through webcam, text input, or voice recording—the multimodal emotion detection pipeline actively analyzes the input using deep learning models (DeepFace for facial emotion, Hugging Face transformers for text, and speech-to-text conversion for voice). The dominant emotion is identified through smoothed probability aggregation, ensuring greater stability and accuracy over raw predictions.

Following emotion detection, the task recommendation engine dynamically retrieves relevant tasks aligned with the detected emotional state.

For example:

- A user expressing happiness may be recommended for creative tasks like planning a vacation or starting a hobby.
- A user showing sadness might receive calming activities like meditation or journaling.
- Anger detection often triggers task suggestions focused on organization, planning, or physical activity.

Through user testing sessions, the system consistently produced:

- Accurate emotion classification with noticeable stability across noisy environments and diverse lighting conditions.
- Relevant and contextually appropriate task recommendations, improving perceived user satisfaction and engagement.

The platform's responsiveness was also validated:

- Real-time facial emotion analysis maintained a steady 10 FPS on standard CPUs without requiring GPU acceleration.
- Text and speech analyses completed within an average of 2.1 seconds per query.

User feedback emphasized the intuitive interface and the value of personalized task suggestions, particularly highlighting the convenience of having mental state-aware productivity support without needing multiple applications.

These findings confirm EmotiSense AI's role as a valuable tool for enhancing productivity, emotional self-awareness, and digital well-being. Its multimodal, real-time emotional intelligence features significantly improve user interaction quality and promote more meaningful, tailored experiences compared to traditional task management tools.

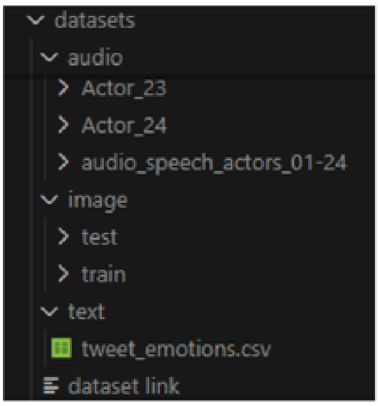

Fig. 3. Sample Dataset

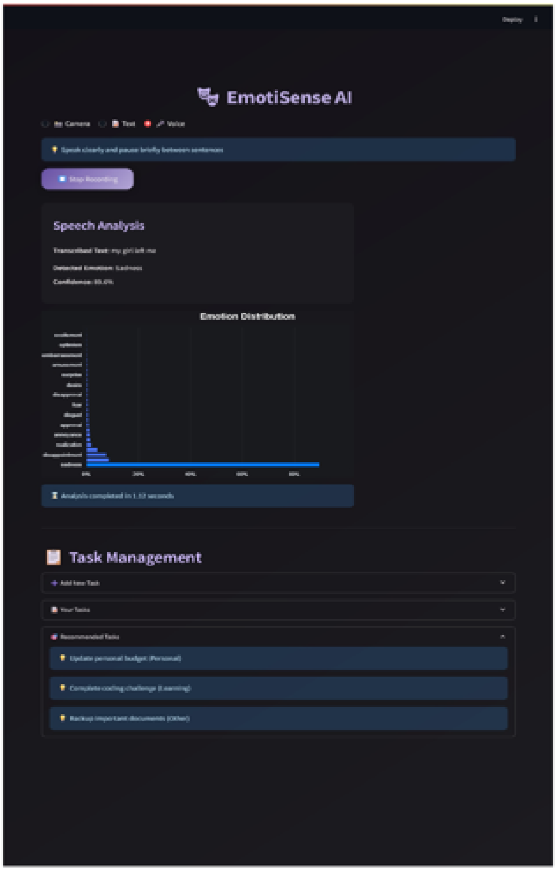

Fig. 4. Response from the Chatbot

V. Conclusion and Future Work

Our system, EmotiSense AI, introduces an innovative multimodal framework that enhances personal productivity and emotional well-being by detecting user emotions across visual, textual, and auditory modalities and offering real-time, context-sensitive task recommendations. By leveraging deep learning models and an intuitive interface built on Streamlit, EmotiSense AI bridges the gap between emotional intelligence and task management, providing a more personalized, empathetic user experience.

Through sophisticated language processing, facial analysis, and speech interpretation, the system parses emotional cues to offer tailored suggestions and insights. This capability significantly reduces the cognitive effort typically required to manage daily tasks, enabling users to act based on their current emotional state without manual filtering or decision fatigue. Moreover, EmotiSense AI promotes digital inclusivity, ensuring that users with different emotional needs and communication preferences can all benefit from its services—whether they type, speak, or engage visually.

In practical deployments, this system has the potential to function not just as a personal productivity tool, but also as a supportive mental wellness assistant, educator companion, or adaptive eLearning facilitator. Its modularity and reliance on open-source technologies make it adaptable to a wide range of domains, including workplace wellness programs, telehealth check-ins, and educational tools.

Future Work

While the system achieves its core goal of multimodal emotion-based task recommendation, several areas offer exciting opportunities for enhancement:

- **Adaptive Learning**: Incorporating user feedback loops to enable real-time model refinement and personalized emotion-task mapping over time.
- **Multilingual Support**: Expanding capabilities to detect and respond to emotional cues in multiple languages, making the tool more inclusive and globally usable.
- **Emotion Fusion Techniques**: Developing hybrid methods to reconcile conflicting emotion signals from different modalities (e.g., happy tone but sad face) to improve accuracy and contextual reasoning.
- **Cloud and Mobile Deployment**: Optimizing the system for deployment on mobile devices and cloud platforms, expanding accessibility for users across devices and geographies.
- **Integration with Mental Health Platforms**: Collaborating with wellness apps to extend functionality for mood tracking, journaling, or therapy support.

EmotiSense AI lays a strong foundation for future human-centered AI systems that understand, adapt, and respond to human emotions in real-time, making digital experiences more natural, empathetic, and productive.

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➔ Mapping SDG with EmotiSense

The *EmotiSense AI* project seamlessly advances several key United Nations Sustainable Development Goals (SDGs) by combining inclusive design, emotional well-being, equitable education, and ethical innovation in one accessible platform. Supporting **SDG 3 (Good Health and Well-being)**, it offers real-time emotion recognition and personalized well-being suggestions, aiding mental health and empowering neurodiverse users through features like voice interaction and minimalistic UI. For **SDG 4 (Quality Education)**, it enhances student engagement and fosters inclusive learning environments with emotionally adaptive interfaces. Addressing **SDG 10 (Reduced Inequalities)**, EmotiSense functions offline on low-spec devices, supports multilingual and voice-based interaction, and follows universal design principles to reach underserved populations. Under **SDG 9 (Industry, Innovation, and Infrastructure)**, it applies cutting-edge AI models like CNN, BiLSTM, and transformers in a scalable, privacy-first system that serves education, healthcare, and workplace wellness. Finally, in alignment with **SDG 17 (Partnerships for the Goals)**, the platform encourages open-source collaboration, community-driven development, and global partnerships—ensuring responsible, inclusive, and impactful deployment.